Quantifying Strategic Dependence

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Abstract

We develop a Strategic Dependency Index (SDI) to quantify the welfare cost of product-level import price shocks. Unlike existing empirical indicators based on concentration metrics and ad hoc thresholds, the SDI is derived from a structural cost-of-living framework, and allows for additive decomposability across products, source countries and destination countries. We apply the SDI to the EU27, and estimate trade elasticities, love-for-variety parameters, and origin-destination-specific taste shifters using highly disaggregated 8-digit product-level trade data over 2002–2021, instrumenting for prices and expenditure shares to address endogeneity. Three sets of findings emerge. First, the products generating the largest welfare losses are petroleum oils, liquefied natural gas, iron ores, and selected basic metals. Their strategic relevance stems from the interaction of both low substitutability across sources and large expenditure shares. Second, strategic dependency varies sharply across EU member states even for the same product, driven by fundamentally different channels — high substitution elasticities in some countries versus large expenditure shares in others — implying that uniform EU-wide policy responses may fail to address the heterogeneous sources of vulnerability. Third, the suppliers contributing most to aggregate welfare exposure do not coincide with the geopolitical rivals dominating policy discourse: China, the USA, and Russia do not lead the SDI ranking. The SDI provides a tractable, theory-consistent framework for evaluating targeted policy interventions aimed at reducing strategic trade exposure.

Keywords: Strategic trade dependence, import vulnerability, welfare costs.
JEL codes: F11, F13, F14, D12, D60.

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1 Introduction

Recent disruptions to international trade have renewed interest in countries' exposure to foreign shocks. In a broad class of trade models, the welfare impact of such shocks depends on expenditure shares and elasticities of substitution across suppliers (e.g. Broda and Weinstein (2006); Arkolakis et al. (2012); Amiti et al. (2019); Lashkaripour and Lugovskyy (2023)). Despite this, most empirical measures of strategic trade dependence rely on readily observable concentration metrics such as import shares, Herfindahl indices, or ad hoc threshold rules, which abstract from key demand primitives and therefore do not map into the welfare consequences of trade shocks.

We introduce the Strategic Dependency Index (SDI), a welfare-based measure of trade vulnerability that quantifies the sensitivity of consumer prices to global supply shocks. The SDI is defined as the elasticity of the cost-of-living index with respect to import price changes, weighted by expenditure shares in domestic absorption. It has a direct interpretation: an SDI of 0.37 for petroleum oils for example, means that a 10% increase in its import price raises the aggregate EU cost of living by 3.7%. Unlike existing concentration metrics, the SDI is theory-consistent, continuous, and does not rely on ad hoc thresholds. Its additive structure allows for transparent decomposition across products, EU member states, and extra-EU source countries, making it suitable both as a measurement device and as a framework for counterfactual welfare analysis.

This paper makes three contributions. First, we derive the SDI from a nested CES demand system that isolates three sets of structural demand primitives: trade elasticities governing substitution across source countries, love-for-variety parameters capturing substitution across varieties within industries, and origin-destination-specific taste shifters reflecting persistent non-price determinants of demand. By anchoring the index in a cost-of-living framework, the SDI maps these primitives into a tractable welfare measure. Second, we estimate these parameters at high granularity using 8-digit product-level trade data for all EU27 countries and their global trading partners over 2002–2021. Identification relies on export prices to non-EU destinations as instruments for import prices, following the logic of Autor et al. (2013), and count-based instruments for expenditure shares, following Khandelwal (2010) and Lashkaripour and Lugovskyy (2023). The resulting estimates reveal large heterogeneity in substitution elasticities and taste shifters — both across and within broad industry categories — implying that exposure to foreign suppliers cannot be inferred from import shares alone. Third, we provide a counterfactual framework that quantifies the welfare cost of import price shocks and allows to decompose these costs by product, destination, and source country. We apply this to two exercises: a uniform 10% price shock across all extra-EU imports, and a targeted shock to goods classified as Critical Raw Materials under the EU Critical Raw Materials Act (European Union (2024)).

Three sets of empirical findings emerge from these exercises. First, the products generating the largest welfare losses — petroleum oils, liquefied natural gas, iron ores, and selected basic metals — partly overlap with but also substantively depart from goods flagged by conventional indicators. The SDI identifies basic metals as highly strategic despite their moderate import concentration, while many goods in textiles, food, and NEC manufacturing that rank high under concentration-based measures prove less welfare-relevant due to their high substitutability. Only four of the top-30 SDI products are classified as strategic under the European Commission's composite indicator (European Commission (2021)), and the SDI ranking is far more stable: 22 of the top-30 products in 2019 also appeared in 2002, compared to only 23% of goods retaining their strategic classification under threshold-based measures. Similarly, evaluating Critical Raw Materials through the lens of the SDI reveals that while a handful of CRMs rank among the most strategically dependent goods, the vast majority generate modest welfare effects — their high supply risk notwithstanding — because they account for very small shares of total EU domestic absorption. Second, disaggregating by EU member state reveals sharp cross-country variation in strategic dependency, even for the same product, driven by fundamentally different channels: high price elasticities in some countries versus large expenditure shares in others. This heterogeneity implies that uniform EU-wide policy responses may fail to address the diverse sources of member states' vulnerabilities. Third, decomposing the SDI by extra-EU source country shows that the suppliers contributing most to aggregate welfare exposure — Iraq and Azerbaijan for petroleum, Nigeria and Qatar for natural gas, Brazil and South Africa for iron ores — do not necessarily coincide with the geopolitical context that dominates contemporary policy discourse: China, the USA, and Russia do not dominate the top of the SDI ranking, as EU dependency on these countries is concentrated in specific product categories rather than in the broad sectors where their import shares are highest.

These findings carry direct policy implications. For products where strategic dependency is driven primarily by large expenditure shares — such as petroleum oils — diversification of extra-EU sources is a viable strategy, as substitution across suppliers is relatively easy. For products with low substitution elasticities — such as mining products and certain critical raw materials — diversification alone may prove insufficient, and policies targeting domestic capacity, recycling, or alternative materials may be more effective.

This paper contributes to a growing literature on trade vulnerability and strategic dependence. Existing indicators typically assess dependency using concentration metrics, often combined with threshold rules to classify goods as strategic (e.g. European Commission (2021); Amaral et al. (2022); Guinea and Sharma (2022); Jaravel and Méjean (2022); Baur and Flach (2022); Berthou et al. (2024)). By construction, these measures do not account for product substitutability or preferences for particular sources. As a result, many goods identified as strategic belong to industries with high elasticities of substitution, where demand can be readily reallocated away from disrupted suppliers despite high observed concentration (see e.g. Imbs and Méjean (2015); Fontagné et al. (2022)). Moreover, threshold-based indicators are highly sensitive to short-run fluctuations in trade flows: products may be classified as strategic in one year but not the next, depending on whether concentration metrics cross arbitrary cutoffs (Vicard and Wibaux (2023)). Such volatility is difficult to reconcile with the notion of persistent, structural trade dependence—for example on critical raw materials—and obfuscates welfare-based evaluation and policy analysis. The SDI addresses both shortcomings by grounding strategic dependency in structural demand parameters that are persistent, estimated from data, and directly mapped to welfare.

The rest of the paper is organized as follows. Section 2 provides the theoretical foundation for the SDI. Section 3 describes the data, while Section 4 discusses identification and provides demand parameter estimates. Section 5 quantifies EU strategic dependency through two counterfactual exercises. Section 6 compares the SDI with existing empirical measures, and Section 7 concludes.

2 Theoretical framework

This section develops the theoretical backdrop underlying the Strategic Dependency Index (SDI). We specify a flexible nested constant elasticity of substitution (CES) demand system that characterizes consumer preferences as in Lashkaripour and Lugovskyy (2023). The framework isolates three key demand primitives, all of which are allowed to vary across industries, and which jointly determine consumers' exposure to foreign shocks: substitution elasticities across origins, substitution elasticities across varieties, and origin-destination-specific taste shifters. We then define the SDI as a welfare-based measure derived from a cost-of-living index, quantifying the sensitivity of consumer prices to source-specific disruptions as a transparent mapping from demand parameters to strategic dependency. Additional derivations are provided in Appendix A.

2.1 Preferences and demand

Consider an endowment economy with multiple countries $i, j \in C$, industries $k \in K$, and time indexed by t.

$$\max_{\{Q_{i,kt}\}_{k\in K}} U_{i,t}(Q_{i,1t}, ..., Q_{i,Kt}),$$

subject to her budget constraint $\sum_{k\in K} P_{i,kt}Q_{i,kt} = Y_{i,t}$, where $Q_{i,kt}$ denotes consumption of industry k goods, $P_{i,kt}$ is the corresponding price index, and $Y_{i,t}$ is total expenditure, taken as given.

Each $Q_{i,kt}$ is a CES aggregator of industry k goods sourced across supplying countries j:

$$Q_{i,kt} = \left[\sum_{j\in C} \alpha_{ji,kt}^{\frac{1}{\sigma_k}} Q_{ji,kt}^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}},$$

where $Q_{ji,kt}$ denotes industry k goods produced in country j and consumed in country i at time t. The associated price index is $P_{i,kt} = \left(\sum_{j\in C} \alpha_{ji,kt} P_{ji,kt}^{1-\sigma_k}\right)^{\frac{1}{1-\sigma_k}}$, with $\sigma_k > 1$ the elasticity of substitution across origin countries for industry k goods, reflecting Armington differentiation by country of origin, and $\alpha_{ji,kt}$ is an origin-destination-industry-specific preference shifter, capturing consumers' taste in country i for goods k from source country j. This taste shifter captures the non-price determinants of demand, such as perceived quality, reputation, or geopolitical ties, and is allowed to vary over time.

In turn, the bundle $Q_{ji,kt}$ aggregates the demand for varieties of goods within an origin-destination-industry tuple:

$$Q_{ji,kt} = \left[\int_{\omega\in\Omega_{ji,kt}} \phi_{ji,kt}(\omega)^{\frac{1}{\gamma_k}} q_{ji,kt}(\omega)^{\frac{\gamma_k-1}{\gamma_k}} d\omega\right]^{\frac{\gamma_k}{\gamma_k-1}},$$

where $q_{ji,kt}(\omega)$ is the quantity consumed of variety ω within industry k goods produced in j and consumed in i at time t, $\gamma_k \geq \sigma_k > 1$ is the elasticity of substitution across varieties within industry k, and $\phi_{ji,kt}(\omega)$ is a variety-specific taste shifter. The associated price index is $P_{ji,kt} = \left[\int_{\omega\in\Omega_{ji,kt}} \phi_{ji,kt}(\omega) p_{ji,kt}(\omega)^{1-\gamma_k}\right]^{\frac{1}{1-\gamma_k}}$, where $p_{ji,kt}(\omega)$ is the price of variety ω. The demand for each individual variety ω of industry k produced in j and consumed in i at time t is then given by:

$$q_{ji,kt}(\omega) = \phi_{ji,kt}(\omega) \left[\frac{p_{ji,kt}(\omega)}{P_{ji,kt}}\right]^{-\gamma_k} \alpha_{ji,kt} \left[\frac{P_{ji,kt}}{P_{i,kt}}\right]^{-\sigma_k} Q_{i,kt}. \tag{1}$$

This nested CES formulation provides a tractable yet flexible framework to quantify several key margins of trade-related strategic dependence. It identifies four parameters of interest at the level of individual industries k: (i) σ_k, governing substitutability across source countries and corresponding to the trade elasticity $\sigma_k - 1$; (ii) γ_k, measuring substitutability across varieties within industries and reflecting consumers' love for variety; (iii) $\alpha_{ji,kt}$, capturing an origin–destination–industry taste shifter reflecting non-price components of demand; and (iv) $\phi_{ji,kt}(\omega)$ as variety-specific taste shifters. Together, these demand primitives fully characterize the elasticity of the SDI with respect to source-specific price shocks below.

2.2 The Strategic Dependency Index

Next, we define a measure of strategic dependency that quantifies consumers' welfare changes in response to foreign price shocks. Under homothetic preferences, the first-order change in the cost-of-living index equals the welfare effect of a price change for a given variety, weighted by its expenditure share, while holding nominal income fixed. The welfare cost for country i of a price shock affecting variety ω in industry k is then given by:

$$SDI_{i,kt}(\omega) = \frac{y_{i,kt}(\omega)}{y_{i,t}} \sum_{j \in C} \frac{\partial \ln P_{i,kt}}{\partial \ln p_{ji,kt}(\omega)}. \tag{2}$$

where $\frac{y_{i,kt}(\omega)}{y_{i,t}}$ denotes the expenditure share of variety ω of industry k in total consumption in i at t, and $\frac{\partial \ln P_{i,kt}}{\partial \ln p_{ji,kt}(\omega)}$ is the elasticity of the sectoral price index to a price change in that variety.[1] Eq. (2) therefore represents the marginal welfare cost of a proportional price increase in variety ω affecting all source countries j simultaneously. Since the sectoral price index is defined as:

$$P_{i,kt} = \left(\sum_{j \in C} \alpha_{ji,kt} \left(\int_{\omega \in \Omega_{ji,kt}} \phi_{ji,kt}(\omega) p_{ji,kt}(\omega)^{1-\gamma_k} \right)^{\frac{1-\sigma_k}{1-\gamma_k}} \right)^{\frac{1}{1-\sigma_k}}, \tag{3}$$

the price index elasticity depends on the four demand primitives modeled above: the trade elasticity $\sigma_k - 1$, the within-industry elasticity γ_k, the origin-specific preference shifter $\alpha_{ji,kt}$, and the variety preference shifter $\phi_{ij,kt}(\omega)$. Lower values of σ_k and γ_k imply less substitutability across sources or varieties, amplifying the welfare impact of price shocks. Higher values of $\alpha_{ji,kt}$ and $\phi_{ij,kt}(\omega)$ increase exposure to shocks originating from that source or variety, respectively, by raising its weight in the price index at time t.

The SDI has a direct elasticity interpretation. It measures the percentage increase in the EU cost-of-living index resulting from an increase in the price of a given product. The SDI thus quantifies the welfare costs for consumers in i at time t for changes in prices of varieties ω from source countries j in industries k. It combines exposure to price shocks through structural demand parameters with a product's economic importance in consumption. The additive structure of the SDI allows for straightforward partitioning of the cost of living into (sub-)sets of products, source countries, destinations, or any combination of these.

In the empirical application, we quantify the SDI for the EU27 and its member states. We therefore also aggregate welfare costs across consuming countries for each variety ω to obtain an aggregate measure of strategic dependency:

$$SDI_{kt}(\omega) = \sum_{i} \frac{y_{i,t}}{y_t} SDI_{i,kt}(\omega), \tag{4}$$

where $\frac{y_{i,t}}{y_t}$ denotes country i's share in total aggregate expenditure.

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[1] Since the price index is homogeneous of degree one, the sum of its elasticities with respect to underlying prices equals one from Euler's theorem for homogeneous functions.

Finally, the SDI can be disaggregated across supplying countries j for each variety ω:

$$SDI_{j,kt}(\omega) = \sum_i \frac{y_{i,kt}(\omega)}{y_t} \frac{\partial \ln P_{i,kt}}{\partial \ln p_{ji,kt}(\omega)}, \tag{5}$$

which identifies the contribution of each source country to the aggregate welfare cost for variety ω.

3 Data and descriptive statistics

We apply the methodology of the SDI to the EU27 and construct a panel dataset of detailed product-level trade flows between all EU27 member states and their global trading partners over the period 2002–2021 to recover prices and quantities, and to estimate the demand parameters, together with a panel of product-country-year expenditures to quantify consumption shares. The resulting dataset comprises nearly 48 million annual observations on trade values, quantities, unit values, and domestic expenditures.

3.1 Data sources and construction

We combine three main data sources: (i) Eurostat's Comext with country-pair trade flows at the 8-digit product level for flows including EU member states as a reporter or partner, (ii) CEPII's BACI to obtain information on other country-pair flows, and (iii) OECD's ICIO tables to recover domestic expenditure shares.

First, we use the Comext database to obtain harmonized annual import flows at the product level for all EU27 countries and their global trading partners. Throughout, we define the EU as the current EU27 composition for all years in the sample. The United Kingdom is therefore treated as an extra-EU partner over the entire period to ensure consistency over time. Each EU country reports monthly import values and quantities with each of its trade partners at the 8-digit Combined Nomenclature (CN8) level, covering around 7,800 unique products.[2] Import values include costs, insurance, and freight (CIF), all in current euros. We first aggregate monthly observations to yearly values. Next, to address changes in product codes over time, we follow Pierce and Schott (2012) and Van Beveren et al. (2012), and construct stable CN8+ codes using product concordances from Eurostat's CIRCABC database. This procedure yields time-consistent CN8+ product codes that allow us to track identical goods over the entire panel, which is essential for estimating the various demand parameters.[3] As is standard in the literature, we use unit values (i.e., values over quantities) as proxies for prices, while acknowledging that they may reflect compositional variation within narrowly defined products (e.g., Feenstra (1994), Broda and Weinstein (2006), Simonovska and Waugh (2014a), Giri et al. (2021)).

Next, we use CEPII's BACI dataset with information on annual product-level trade flows at the Harmonized System 6-digit (HS6) level across countries worldwide between 2002 and 2021. We extract export flows for all extra-EU country pairs, which will be used to construct instrumental variables in Section 4.

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[2] CN8 products are defined as an EU-specific 2-digit extension of the global Harmonized System (HS) codes at the 6-digit product level from the World Customs Organization. Countries in Comext are defined as UN recognized sovereign countries, non-sovereign territories, and customs territories and regions. We exclude customs territories and regions, as well as any aggregates.

[3] HS product codes can change due to statistical re-classifications of products over time, coordinated by the World Customs Organization, which are adopted in the CN8 product codes used by EU member states. Changes in codes are not always one-to-one, but may be one-to-many, many-to-one, or many-to-many, requiring careful mapping of product codes over time (see also e.g., Magerman (2022)).

Finally, we use domestic expenditure data from the OECD ICIO tables, covering the years 2002–2019 (the latest year available with the ICIO tables 2023 release). These data report domestic and international trade flows for 45 ISIC industries (supplying and using) for each of the EU27 member states. It allows us to measure total domestic absorption, calculated as domestic production plus imports and aggregated over all using sectors for each EU country. Domestic absorption is then matched to Comext data to obtain domestic expenditure shares of products for the construction of the SDI.

3.2 Descriptive statistics

We first provide some details on the final datasets and the evolution of trade flows and their concentration over time. The main variables used in our analysis are summarized in Table 1. The annual dataset covers almost 48 million CN8-source-destination-year observations. Import values are highly right-skewed: the yearly mean import value is 1.5 million euro, while the median is only 21,000 euro. This also holds in real terms for import quantities, with a mean of 1,223 tonnes and a median of just 2 tonnes. This skewness also remains in relative terms: while the median import share of products, within a given origin-destination-sector, is 0.2%, the mean is 6%, with shares above 13% at the 90th percentile. By contrast, the number of origin countries for a given destination-product-year and the number of imported products by origin-destination-sector-year are less dispersed, with mean values of 13 and 16, respectively. These patterns already suggest a substantial degree of import concentration in EU trade relationships, as the large gap between mean and median import shares indicates that a small number of origin–product pairs account for a disproportionate share of total import expenditure within each sector. Combined with relatively few supplying countries per product, this points to concentrated import shares, where disruptions to a single dominant supplier could significantly affect consumer welfare.

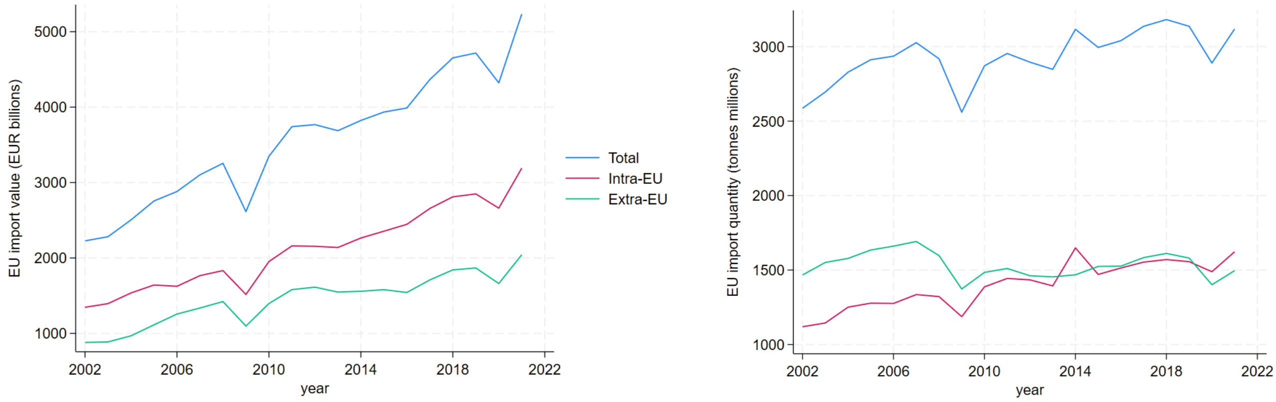
Table 1: Summary statistics (pooled, 2002-2021).

				percentiles				
Variable	N	Mean	St. Dev	p10	p25	p50	p75	p90
Import value (th. EUR)	47,968,504	1,485	35,605	0.3	2.2	20.8	182.5	1,171
Import quantity (tonnes)	47,968,504	1,223	71,295	0.0	0.1	2.0	28.2	270.2
Import price (th. EUR/tonnes)	47,968,504	229	97,659	1.1	3.0	9.9	32.8	102.2
Product import share (%)	47,968,504	6.2	0.2	0.0	0.0	0.2	2.0	13.6
Number of origin countries	3,715,005	12.9	12.6	2	4	9	18	29
Number of products	2,992,682	16.0	35.1	1	2	4	15	40
Origin-country export price (th. EUR/tonnes)	3,410,899	559	80,985	0.7	2.1	6.5	20.8	60.2
Domestic expenditure (bil. EUR)	486	274	426.0	15.8	31.0	122.9	255.1	1,015.8

We also examine the evolution of EU imports over time. Figure 1 plots the total value and quantity of imports from intra-EU and extra-EU origins between 2002 and 2021. The overall import value of EU27 countries (panel a) more than doubled in nominal terms during this period, from approximately 2 trillion euro in 2002 to over 5 trillion euro in 2021. Intra-EU imports account for around 60% of this total in 2021 and has grown more rapidly than extra-EU imports since the 2008 global financial crisis. In real terms (panel b), total import quantities exhibit a flatter trend, reaching over 3 billion tonnes in 2021. Initially, extra-EU import volumes exceeded those from within the EU, but this gap narrowed substantially after 2008. This widening gap likely reflects both the deepening of the EU Single Market and a post-crisis reorientation of global supply toward geographically closer partners, consistent with a broader trend of a slowdown in globalization during the post-crisis period (Constantinescu et al. (2015); Baldwin (2016); Antràs (2020)). Yet, extra-EU imports remain significant, representing about 40% of total import value and nearly half of total import quantity as of 2021.

Finally, Figure 2 provides further detail on the composition of extra-EU imports and plots the share of import value for the top five non-EU trading partners over time. These top countries consistently jointly account for more than half of total extra-EU import value, yet both the composition and relative contributions of the group have changed drastically over the sample period. Japan, which ranked among the top 5 extra-EU suppliers in 2002, had fallen out by 2021, and has been replaced by Russia, reflecting the EU's growing dependence on Russian energy imports prior to the 2022 geopolitical rupture. Within the top five, the shifts in relative contributions are substantial. In 2002, the United Kingdom was the largest extra-EU supplier under the EU27 definition, followed by the United States. By 2021, China's share had risen from 8% to 23%, making it by far the dominant extra-EU trading partner. These dynamics underscore that EU dependence on third countries is not only concentrated among a small number of suppliers, but also that the identity and relative importance of those suppliers can shift substantially over time.

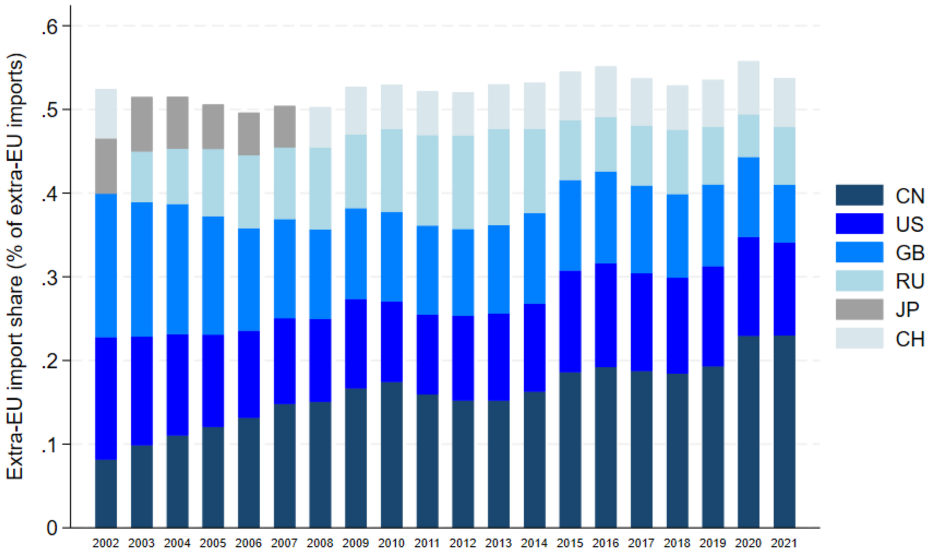
Figure 1: EU imports by EU and extra-EU origin countries (2002-2021).



(a) Import value

(b) Import quantity

Figure 2: EU imports from top-5 extra-EU countries (2002-2021).



4 Estimation and identification

We now estimate the various demand parameters from Section 2 using the data constructed in Section 3. We log-linearize the variety-level demand equation and estimate it by two-stage least squares (2SLS), both pooled and separately for each industry k. Identification relies on an instrumental variable strategy to isolate exogenous variation in both prices and expenditure shares. These estimates provide the key demand primitives required to construct the SDI. In particular, heterogeneity in substitution elasticities and taste shifters governs the welfare impact of source-specific price shocks and therefore underpins the ranking of strategically important products in the subsequent sections.

4.1 Parameter estimation

To estimate the specified demand parameters, we log-linearize the variety-level demand equation in Eq. (1), yielding the following estimating equation:

$$\ln x_{ji,kt}(\omega) = (1-\sigma_k)\ln p_{ji,kt}(\omega) + \left(1 - \frac{\sigma_k - 1}{\gamma_k - 1}\right)\ln \lambda_{ji,kt}(\omega) + \ln \delta_{i,kt} + \ln \alpha_{ji,k} + \ln \phi_{ji,k}(\omega) + \ln \varepsilon_{ji,kt}(\omega). \tag{6}$$

Here, $x_{ji,kt}(\omega) \equiv p_{ji,kt}(\omega) q_{ji,kt}(\omega)$ denotes the import value of variety ω, and $p_{ji,kt}(\omega)$ is its import price. The term $\lambda_{ji,kt}(\omega) \equiv \frac{x_{ji,kt}(\omega)}{\sum_{\omega \in \Omega_{ji,kt}} x_{ji,kt}} = \phi_{ji,kt}(\omega)\left[\frac{p_{ji,kt}(\omega)}{P_{ji,kt}}\right]^{1-\gamma_k}$ denotes the expenditure share of variety ω within industry k imports from country j to country i at time t. Further, $\delta_{i,kt} \equiv P_{i,kt}^{\sigma_k} Q_{i,kt}$ captures destination–industry–time demand shifters and is absorbed by destination–industry–year fixed effects. We assume that the origin-destination-industry taste shifter $\alpha_{ji,kt}$ can be decomposed into a time-invariant component $\alpha_{ji,k}$ and a time-varying component $\tilde{\alpha}_{ji,kt}$. We are interested in $\alpha_{ji,k}$, as it represents the persistent preferences for goods in the destination country from a specific source country over time, and is estimated using country-pair-industry fixed effects. Similarly, $\phi_{ji,kt}(\omega)$ can be decomposed into a time-invariant component $\phi_{ji,k}(\omega)$ and a time-varying component $\tilde{\phi}_{ji,kt}(\omega)$, where the time-invariant variety-specific demand shifter is estimated using origin–destination–industry–variety fixed effects. The residual $\varepsilon_{ji,kt}(\omega)$ collects time-varying demand shocks $\tilde{\alpha}_{ji,kt}$ and $\tilde{\phi}_{ji,kt}(\omega)$, as well as other unobserved factors that are uncorrelated with the regressors. These time-invariant taste shifters are precisely the object of interest for measuring structural trade dependence: by construction, they capture the non-price determinants of demand that are stable across the sample period, and it is this stability that contributes to the temporally consistent SDI rankings documented in Section 5.

We define product varieties as is standard in the literature (e.g., Feenstra (1994), Broda and Weinstein (2006), Caliendo and Parro (2015)): a variety ω is identified at the product (CN8) level, sourced from any origin country j to any EU destination country i in sector k and year t. I.e., a variety is differentiated across CN8 products within the same industry, as well as by origin-destination country pair. The industry k index is assigned to ISIC industries or HS 2-digit aggregate products in different quantifications below. Finally, $x_{ji,kt}(\omega)$ and $p_{ji,kt}(\omega)$ are directly observable in the data, while $\lambda_{ji,kt}(\omega)$ is calculated from observed country-pair-sector imports.

4.2 Identification strategy

The estimation of the demand parameters from trade data is subject to well-known endogeneity concerns. In particular, both prices $p_{ji,kt}(\omega)$ and expenditure shares $\lambda_{ji,kt}(\omega)$ are likely to be endogenous to unobserved demand shocks: higher demand for a given variety may raise its observed import price and increase its expenditure share, leading to biased estimates of substitution elasticities if these variables are treated as exogenous. To address this, we implement an instrumental variables strategy that isolates exogenous variation in both prices and expenditure shares.

We first address the endogeneity of prices. Unobserved positive (negative) demand shocks may lead to both higher (lower) import quantities and higher (lower) prices, inducing a positive correlation between the observed import price $p_{ji,kt}(\omega)$ and the error term in Eq. (6), biasing estimates of the trade elasticity $\sigma_k - 1$ towards zero. We therefore employ an approach similar to Autor et al. (2013) and construct an instrument based on the weighted average export price of variety ω from origin country j to non-EU destinations at time t, with weights given by the export value of that product to each destination:

$$p^{e}_{j,kt}(\omega) = \sum_{i \in EX} \frac{x_{ji,kt}(\omega)}{x_{j,kt}(\omega)} p^{e}_{ji,kt}(\omega), \tag{7}$$

where $p^{e}_{ji,kt}(\omega)$ is the export price from country j to each non-EU country $i \in EX$, $x_{j,kt}$ is the total export value of ω in k from j to all non-EU countries, and the weights $\frac{x_{ji,kt}(\omega)}{x_{j,kt}(\omega)}$ reflect the share of exports to that destination. The identifying assumption for the price instrument is that export prices of a given variety to non-EU destinations are orthogonal to EU-specific demand shocks, conditional on covariates. By excluding EU destinations from the construction of the instrument, we isolate the supply-driven components of export prices, such as cost shocks, productivity, or quality differences, that are common across non-EU countries and plausibly exogenous to EU-specific demand shocks. A remaining concern is the presence of aggregate demand shocks that are correlated across both EU and extra-EU countries. Export prices to extra-EU destinations may then still be affected by unobserved demand shocks that also affect EU imports, violating the exclusion restriction. To mitigate this concern, we include destination-sector-year, origin-destination-sector, and sector-product fixed effects in the first-stage regression, absorbing common demand shocks across markets.[4]

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[4] While some studies use tariffs as instruments for import prices, this strategy is not viable in our setting. First, tariffs may be endogenous to trade flows, for example, if imposed in response to trade shocks or if firms adjust imports in anticipation of tariff changes. Second, EU tariffs on CN8 products are zero for a large share of trade flows (82% of observations in our

Data on export prices at the CN8 product level from the Comext database are only available for EU origin countries. To obtain export prices for all global origin countries, we therefore use unit values at the HS6 level from the BACI database. We restrict the construction of the instrument to HS6 products that can be mapped consistently to CN8 codes over time. While HS6 prices are more aggregated than CN8 prices, this allows us to construct a consistent instrument across all countries. To assess whether this aggregation introduces bias, we also conduct a robustness check using the average CN8-level export price from EU origin countries to extra-EU destinations from the Comext data (see Table A1 in Appendix B). This more granular instrument yields somewhat higher estimates of the trade elasticity for some industries, but the ranking across industries remains nearly identical, suggesting that the HS6-based instrument provides a reliable approximation of supply-side price variation, despite its coarser product definition.

Next, to address the endogeneity of expenditure shares, we construct two instrumental variables similar to Khandelwal (2010) and Lashkaripour and Lugovskyy (2023). Positive demand shocks can simultaneously raise a variety's import value and its expenditure share, reflecting a mechanical correlation between expenditure shares and unobserved demand shocks. The main instrument is the number of origin countries supplying CN8 product ω to EU country i in year t. This count-based measure proxies for exogenous variation in supply-side market access. The identifying assumption for the expenditure-share instrument is that variation in the number of supplying countries affects import demand only through its effect on expenditure shares and is uncorrelated with idiosyncratic demand shocks at the variety level.

Because the instrument varies only at the destination-product-year level, including all three fixed effects causes a practical loss of its residual variation. We therefore consider an additional instrument as also implemented by Lashkaripour and Lugovskyy (2023), that is the number of CN8 products imported from country j to EU country i within industry k in year t. As a robustness check, we use the second instrument alone (see Table A2 in Appendix B). This measure is mechanically correlated with product expenditure shares: the more products a country supplies, the smaller the share of any one product on average, everything else equal. Unlike the main instrument, it varies at the origin-destination-sector-year level and can be used alone with the full set of fixed effects. However, it may be more directly correlated with unobserved determinants of import demand, such as trade policy shifts or structural market changes, potentially violating the exclusion restriction. We therefore interpret this second instrument as complementary. It delivers slightly lower but consistent estimates of love for variety elasticity for most industries, with few exceptions, suggesting that the main instrument captures well the exogenous variation of the expenditure share.

4.3 Demand parameter estimates

We first present average coefficients and then document industry k-specific estimates. Table 2 reports OLS and 2SLS coefficients from estimating Eq. (6) using three different fixed effects specifications. First stage results of the 2SLS specifications are provided in Table A3 in Appendix B. Throughout, standard errors are clustered at the HS2-year level to account for within-industry correlation in demand shocks across origin-destination pairs within a given year. Columns (1) and (2) report results

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data), due to internal EU trade and preferential agreements with many extra-EU partners. Incorporating all zero trade flows would pose computational challenges, particularly in our three-way fixed effects framework, while excluding them could introduce severe selection bias.

using destination-sector-year and origin-destination-sector fixed effects. The OLS estimates in column (1) are statistically significant and have the expected sign, but coefficients are clearly biased toward zero. Similarly, the expenditure share coefficient is biased upward, approaching one. In the 2SLS setup in column (2), the trade elasticity increases in magnitude to -0.6, while the expenditure share coefficient falls to below 0.8. The instruments are highly relevant: the Kleibergen–Paap Wald F-statistic exceeds 2,000, far above the Stock and Yogo (2005) weak-identification critical values (e.g., 13.43 for a maximal IV size of 10% in our sample).

Columns (3) and (4) add origin-destination-sector-variety fixed effects, allowing for fine-grained control of product-specific demand shocks, even within country pairs. While the OLS estimates remain clearly biased, the 2SLS estimates in column (4) reveal a stronger trade elasticity of -1.1 and a much lower expenditure share coefficient of 0.2. The low expenditure share elasticity likely reflects the fact that much of the variation is now absorbed by the granular fixed effects, leading to weaker identification, as these fixed effects absorb a large part of the variation in prices and expenditure shares. Still, the weak identification test comfortably passes standard thresholds with an F-stat of 1.645.

Our preferred specification in columns (5) and (6) replaces the most granular fixed effect with a sector-product fixed effect, which controls for product heterogeneity across all countries without over-saturating the model. The 2SLS estimate in column (6) suggests a trade elasticity of -2.3, implying that a 1% increase in the price of a good reduces EU imports from a given origin by 2.3%. The coefficient on the expenditure share is 0.38, indicating moderate love for variety within industries: a 1% increase in the expenditure share of one variety increases its imports, on average, by about 0.4%. Next, we recover the taste parameters $\alpha_{ji,k}$ from the estimated origin-destination-industry fixed effects, which we normalize so that $\sum_{j\in C}\alpha_{ji,k}=1$. This uniquely identifies the $\alpha_{ji,k}$ and makes them comparable across origin countries.

Table 2: OLS and 2SLS estimation results.

Dependent variable: import value (logs)	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Price, $(1-\sigma_k)$	-0.023***	-0.619***	-0.011***	-1.077***	-0.023***	-2.329***
	(0.001)	(0.023)	(0.002)	(0.059)	(0.002)	(0.042)
Expenditure share, $\left(1-\frac{\sigma_k-1}{\gamma_k-1}\right)$	0.955***	0.759***	0.908***	0.209***	0.946***	0.376***
	(0.001)	(0.011)	(0.002)	(0.004)	(0.001)	(0.004)
Fixed effects						
$FE_{i,kt}+FE_{ji,k}$	YES	YES	-	-	-	-
$FE_{i,kt}+FE_{j,ik}+FE_{ji,k}(\omega)$	-	-	YES	YES	-	-
$FE_{i,kt}+FE_{ji,k}+FE_{k}(\omega)$	-	-	-	-	YES	YES
Number of HS2-year clusters	1,920	1,920	1,920	1,920	1,920	1,920
Weak identification test	-	15,278	-	1,645	-	2,044
Within-R^2	0.92	-	0.83	-	0.90	-
Obs.	43,177,933	29,712,807	41,643,081	28,714,391	43,177,933	29,712,806

Note: Log-linearized structural demand equation eq(6). The estimation is conducted with different fixed effects specifications. Robust standard errors in parentheses are clustered at the HS2-year-level. The weak identification test statistic is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in large multi-dimensional datasets (see Angrist et al. (1996)). The reported R^2 in the OLS estimations corresponds to within-group goodness of fit. *** p-value<0.01.

We now turn to the industry-specific parameter estimates, reported in Table 3. The trade elasticity (column 3) is large in the industries of *"Basic metals"* (4.3), *"Petroleum and mineral fuels"* (3.8), *"Rubber* *and plastics"* (3.6), and *"Paper"* (3.5), while *"Transport equipment"* (1.3), *"Electrical equipment"* (1.6), and *"N.E.C and recycling"* (1.6) are less substitutable across source countries. Similarly, the love for variety elasticity (column 5) is high in *"Basic metals"* (9.5), *"Paper"* (7.6), and *"Petroleum, coal, and mineral fuels"* (7.2), while it is low in *"Transport equipment"* (3.0); *"Electrical equipment"* (3.5); and *"N.E.C and recycling"* (3.7). These estimated trade and love of variety elasticities are also comparable to similar estimations in other datasets (e.g., Lashkaripour and Lugovskyy (2023) for Colombia). Column (6) then reports the estimated taste for extra-EU imports, $\sum_{j\in EX}\alpha_{ji,k}$, averaged across EU destinations. The taste shifter suggests a strong preference for extra-EU imports of *"Petroleum, and mineral fuels"* (0.85) and *"Mining products"* (0.72). *"Fabricated metals"* (0.27), *"Paper"* (0.30), and *"Non-metallic minerals"* (0.32) from extra-EU countries are relatively less attractive to EU consumers, conditional on their price. We also report the weak identification test statistic for each separate estimation in column (8). Again, in all cases, the instruments are highly relevant, comfortably passing standard thresholds.

These elasticities offer an interpretable ranking of industries by their vulnerability to price shocks and substitutability of foreign inputs. Sectors with low substitutability (low σ_k and γ_k) and a high preference for extra-EU imports ($\sum_{j\in EX}\alpha_{ji,k}$) are natural candidates for 'strategic' sectors. In contrast, a classical dependency candidate like *"Petroleum and mineral fuels"* turns out to have a very high extra-EU taste shifter, but also exhibits high elasticities of substitution. This suggests that there is a high relative preference for exta-EU imports of this sector, due to the low production within the EU, but also that it is relatively easy to substitute away towards other supplying countries and/or varieties in response to a shock. Overall, the substantial dispersion in substitution elasticities and taste shifters across products implies that exposure to foreign suppliers cannot be inferred from import shares alone.

While parameters at the ISIC industry level provide a broad view of substitution and dependence patterns, substantial heterogeneity may still exist at the more detailed product level. We therefore also estimate $\sigma_k - 1$, γ_k, and $\alpha_{ji,k}$ at the HS2 level to further explore within-industry variation. Figure 3 to Figure 5 summarize these parameters across HS2 products, highlighting examples of both high and low substitutability and dependence. These product-level parameters show very heterogeneous results within broader ISIC industries. In particular, various HS products classified in the ISIC industries *"Agriculture"*, *"Food"*, *"Chemicals"*, and *"Basic metals"* display very different values from their sector averages. For instance, in the *"Agriculture"* and *"Food"* sectors, the trade elasticity is almost 6 for *"Cereals (HS 10)"* and 4.2 for *"Cocoa products (HS 18)"*, whereas it ranges from about 0 to 1 for *"Live animals (HS 01)"*, *"Meat (HS 02)"* and *"Fish (HS 03)"*. For *"Basic metals"*, *"Iron and steel (HS 72)"*, *"Zinc (HS 79)"*, and *"Tin (HS 80)"* products are highly substitutable, while *"Nickel (HS 75)"* and *"Processed metals (HS 81)"* are much less substitutable. This heterogeneity is central to our framework: the welfare impact of a source-specific price shock is inversely related to the elasticity of substitution. Products with low substitution elasticities generate disproportionately large price index responses and therefore higher strategic dependency under the SDI.

Similarly, in Figure 5, the taste parameter for extra-EU imports is very heterogeneous for *"Food"*, *"Agriculture"*, and *"Chemicals"* products. For example, EU consumers prefer *"Animal-originated products (HS 05)"*, *"Vegetables (HS 07)"*, and *"Fruit and nuts (HS 08)"* sourced from extra-EU countries, compared to *"Dairy products (HS 04)"*, *"Trees and plants (HS 06)"*, and *"Preparations of cereals (HS 19)"*. Certain *"Chemicals"* from extra-EU countries, such as *"Inorganic (HS 28)"* and *"Organic chemicals (HS 29)"*, are also more attractive to EU consumers than others, like *"Pharmaceuticals (HS 30)"* and *"Cosmetic products (HS 33,34)"*. In contrast, other ISIC industries like *"Electrical equipment"*, and *"Transport equipment"*

Table 3: Estimated parameters by ISIC industry.

Sector	ISIC4 codes	$\sigma_k - 1$	$\frac{\sigma_k-1}{\gamma_k-1}$	γ_k	$\sum_{j\in EX}\alpha_{ji,k}$	Obs.	Weak Ident. test
Agriculture	100-999	2.126	0.623	4.411	0.556	1,204,836	299.8
		(0.128)	(0.009)				
Mining	1000-1499	2.489	0.411	7.050	0.723	286,835	132.5
		(0.217)	(0.024)				
Food	1500-1699	2.976	0.668	5.454	0.461	2,762,006	839.5
		(0.107)	(0.014)				
Textiles	1700-1999	1.971	0.650	4.030	0.438	6,350,635	1,828.4
		(0.093)	(0.009)				
Wood	2000-2099	2.884	0.536	6.386	0.368	316,247	158.5
		(0.316)	(0.015)				
Paper	2100-2299	3.546	0.534	7.637	0.303	909,676	181.8
		(0.292)	(0.016)				
Petroleum, mineral fuels	2300-2399	3.778	0.613	7.165	0.852	117,685	33.5
		(0.290)	(0.023)				
Chemicals	2400-2499	2.148	0.646	4.327	0.420	2,620,733	778.1
		(0.042)	(0.007)				
Rubber and plastics	2500-2599	3.583	0.644	6.564	0.377	1,660,561	349.1
		(0.057)	(0.015)				
Non-metallic minerals	2600-2699	2.308	0.583	4.959	0.317	977,489	521.5
		(0.083)	(0.011)				
Basic metals	2700-2799	4.326	0.512	9.450	0.524	1,197,876	98.7
		(0.203)	(0.008)				
Fabricated metals	2800-2899	2.471	0.544	5.539	0.267	2,021,799	161.1
		(0.130)	(0.012)				
Machinery	2900-3099	1.891	0.661	3.863	0.362	2,955,171	113.9
		(0.129)	(0.015)				
Electrical equipment	3100-3399	1.619	0.645	3.508	0.384	2,881,042	814.5
		(0.100)	(0.018)				
Transport equipment	3400-3599	1.291	0.659	2.957	0.419	669,707	61.8
		(0.143)	(0.016)				
N.E.C. and recycling	3600-3800	1.636	0.613	3.669	0.431	1,721,466	241.1
		(0.103)	(0.014)				

Note: The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Parameter $\sum_{j\in EX}\alpha_{ji,k}$ is the sum of preference weights on extra-EU countries, normalized such that $\sum_j \alpha_{ji,k} = 1$ and averaged across EU destinations. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

show more homogeneous parameters across products. EU consumers have a high preference for *"petroleum and mineral fuels (HS 27)"* and *"mining (HS 25,26)"* from extra-EU countries.

Taken together, these results document substantial heterogeneity in the demand primitives governing substitution across foreign suppliers. This heterogeneity is the key driver of variation in the welfare impact of supply shocks across products. In the next section, we combine these estimates with observed expenditure shares to construct the SDI and quantify product-level vulnerability.

Figure 3: Trade elasticity by HS2 product category.

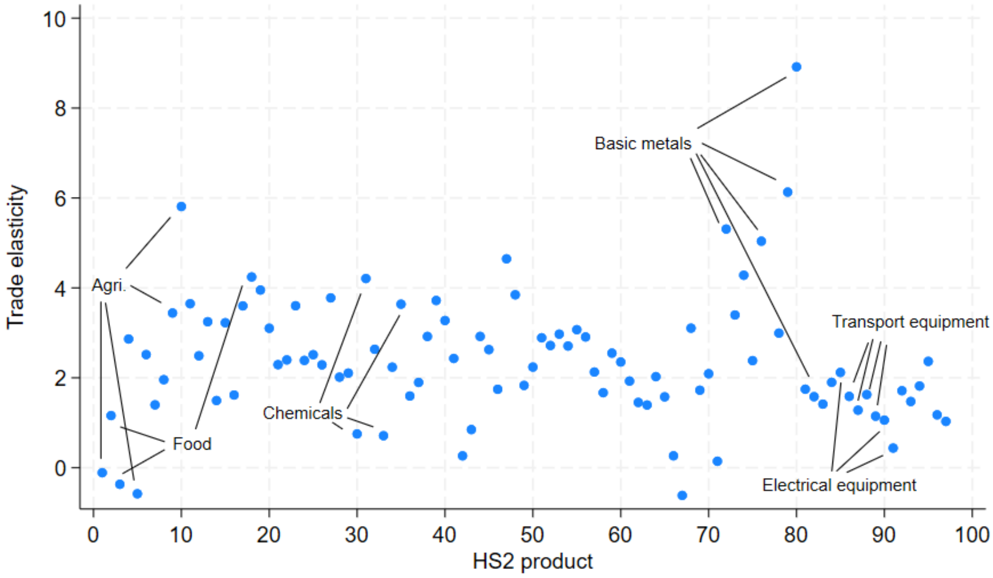
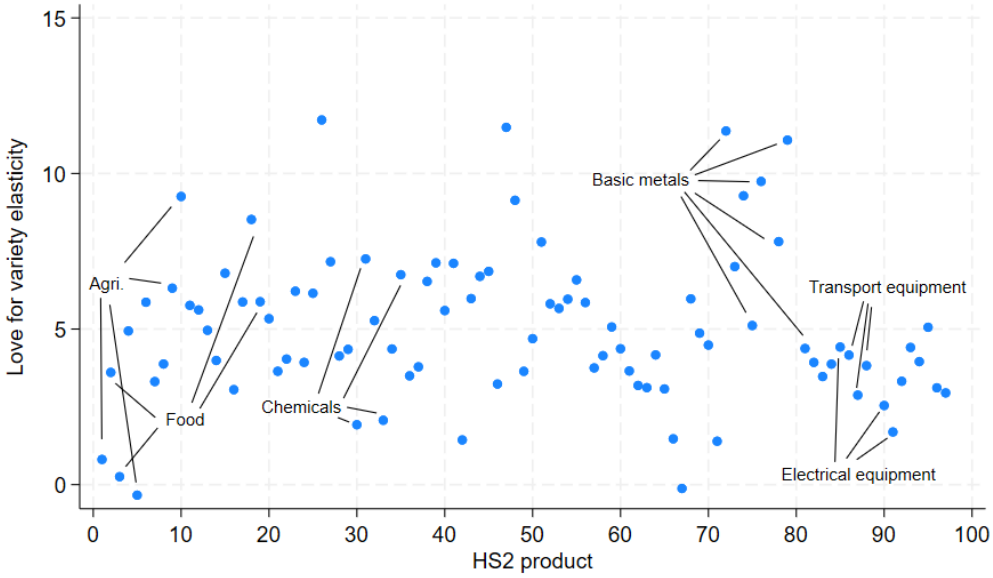


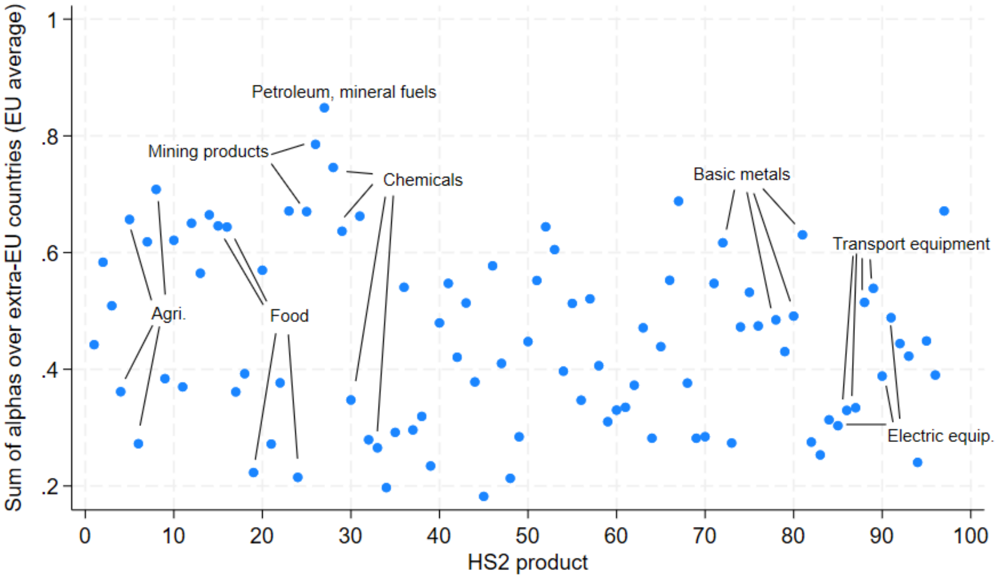
Figure 4: Love for variety elasticity by HS2 product category.



5 Quantifying EU strategic dependency

We use the SDI to quantify the impact of international price shocks on EU welfare in two exercises. The first exercise evaluates an increase of 10% in EU import prices across the board, which could be due to e.g. natural shocks or geopolitical events. We report the top-30 CN8 products with the largest welfare impact and further decompose top products by EU member state and by extra-EU supplying country, respectively. This exercise serves as a validation of the methodology of the SDI, while showcasing its useful additive decomposability. The second exercise quantifies the welfare impact from a 10% increase in import prices of the critical raw materials as identified by the European Critical Raw Materials Act (ECRMA). This allows to further quantify the criticality of various raw materials from a welfare perspective, complementary to their binary identification methodology in the ECRMA.

Figure 5: Taste parameter for extra-EU imports by HS2 product category.



5.1 Uniform change in import prices

For each CN8 product ω, we first apply a 10% increase in import prices from all extra-EU source countries. The price increase is modeled separately for each extra-EU country to consider the marginal contribution of each source country to welfare. The product-level SDI in Eq. (4) provides a transparent benchmark for ranking welfare exposure under a uniform shock, where differences across products are driven entirely by demand primitives and expenditure shares. The additive decomposition in Eq. (5) then recovers source-country contributions to each product's SDI, which is equivalent to isolating the welfare effect of a shock originating from a single supplier. This setup also mimics policy-relevant scenarios, such as increases in trade costs due to e.g. natural disruptions or geopolitical fragmentation.

Column (3) in Table 4 reports the SDI obtained from Eq. (4) for the top-30 products in 2019.[5] The ranking is dominated by three broad product groups. First, varieties in Mineral fuels (HS 27) account for five of the top 30 products, with especially *"Petroleum oils and oils from bituminous minerals"* and *"Natural gas, liquefied"*, showcasing SDI values of 0.367 and 0.045 at rank one and two respectively. An SDI value of 0.367 implies that a 10% increase in a product's price raises the aggregate EU cost of living by around 3.7%, which is quantitatively substantial. Second, several products in Mining (HS 26) also exhibit high SDI values, in particular *"Non-agglomerated iron ores and concentrates"* and *"Aluminium ores and concentrates"*. Third, several products in Basic metals (HS 71–81) appear, including *"Aluminium, not alloyed, unwrought"*, *"Gold, unwrought"*, and *"Copper, refined, in the form of cathodes"*. However, even within HS2 chapters, not all varieties are equally vulnerable. For example, *"Bituminous coal"*, also classified under HS 27, ranks only 21st with an SDI over a hundred times smaller than that of *"Petroleum oils"*. The highest-SDI products – petroleum, liquefied gas, and iron ores – align with intuitive notions of strategic goods, but massive within-group heterogeneity (e.g., petroleum oils vs. bituminous coal) shows that broad product categories are a poor proxy for actual vulnerability.

The SDI is driven by its two main components: the price index elasticity (column 4) and expenditure shares (column 5). Either can have a significant impact on the SDI value of a product, and there is

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[5] The year 2019 is the last year available for domestic expenditures from the OECD ICIO tables (2023 release). All demand parameters are estimated on the pooled sample 2002-2021.

sizable variation in both their absolute and relative contribution to the SDI. For example, high SDI value products with a large price index elasticity but low expenditure share include *"Aluminium ores and concentrates"*, *"Collections and collector's pieces of zoological, botanical, etc."* and *"Crude sunflower-seed oil"*. Conversely, the high SDI for *"Petroleum oils"* is mainly driven by its very large expenditure share rather than its price index elasticity. Similarly for *"Natural Gas"* and *"Oil-cake and other solid residues"*. From the lens of the SDI, this implies that strategic dependency for these types of goods could be significantly lowered if expenditures can be reduced, while close substitutes across supplying countries or similar varieties are in fact readily available.

Finally, the ranking of high SDI products is remarkably stable over time: 22 of the top 30 products in 2019 also appear in the top 30 in 2002 (see Table A4). This suggests that the SDI captures structural dependency characteristics, and is not primarily driven by large changes in trade flows, as is the case with several existing trade indicators discussed in Section 6.

Table 4: Top-30 strategic products (2019).

Product (CN8)	HS2 code	$SDI_{kt}(\omega)$	Price index elasticity	Expenditure share (%)
Petroleum oils and oils from bituminous minerals	27	.367	.118	2.82
Natural gas, liquefied	27	.045	.110	0.16
Non-agglomerated iron ores and concentrates "ECSC"	26	.037	.296	0.07
Coffee (excl. roasted and decaffeinated)	09	.019	.242	0.07
Cocoa beans, whole or broken, raw or roasted	18	.016	.210	0.05
Coking coal "ECSC", whether or not pulverized, non-agglomerated	27	.016	.119	0.06
Aluminium, not alloyed, unwrought	76	.015	.108	0.06
Oil-cake and other solid residues from the extraction of soya-bean oil	23	.011	.070	0.08
Gold, incl. gold plated with platinum, unwrought	71	.009	.050	0.06
Copper, refined, in the form of cathodes and sections of cathodes	74	.007	.065	0.06
Crude palm oil	15	.006	.133	0.01
Aluminium ores and concentrates	26	.005	.377	0.01
Technically specified natural rubber "TSNR"	40	.004	.280	0.01
Anhydrous ammonia	28	.004	.235	0.01
Collections and collector's pieces of zoological, botanical, etc.	97	.004	.558	0.01
Natural gas in gaseous state	27	.004	.008	0.26
Aluminium oxide (excl. artificial corundum)	28	.003	.114	0.01
Non-industrial diamonds unworked or simply sawn, cleaved or bruted	71	.003	.004	0.02
Nickel, not alloyed, unwrought	75	.003	.060	0.03
Linseed (excl. for sowing)	12	.003	.082	0.004
Bituminous coal "ECSC", whether or not pulverized, non-agglomerated	27	.002	.039	0.01
Natural calcium and natural aluminium phosphates, ground	25	.002	.055	0.004
Low erucic rape or colza seeds yielding oil with acid content of < 2%	12	.002	.059	0.03
Bars, rods, wire and sections, (..), of a thickness of > 0,15 mm, of gold	71	.002	.018	0.03
Urea, whether or not in aqueous solution, containing > 45% nitrogen	31	.002	.106	0.01
Crude sunflower-seed oil	15	.002	.304	0.02
Unwrought manganese; manganese powders	81	.002	.073	0.003
Semi-finished products of iron or non-alloy steel	72	.002	.010	0.03
Waste and scrap of silver	71	.002	.024	0.03
Greasy shorn wool, neither carded nor combed	51	.001	.053	0.005

Note: $SDI_{kt}(\omega)$ is the Strategic Dependency Index calculated for each CN8 product ω in sector k and year t. The price index elasticity is computed as the EU weighted average of the price index changes in EU countries. The expenditure share is calculated as the EU expenditure on each good from extra-EU countries in the total EU expenditure (i.e., imports plus domestic production).

Next, we disaggregate the SDI for each EU country and product separately, following Eq. (2). In Figure 6, we show the country-specific SDI for each of the top-4 strategic products. In panel (a), *"Petroleum oils"* shows a high SDI for several EU member states. For Sweden, the Czech Republic, and Greece, this is mostly driven by their high price index elasticity (see Figure A1). Lithuania and Bulgaria, on the other hand, have an average price elasticity but face a large expenditure share, generating a higher SDI (Figure A2). Hence, not only at the product level, but also at the product-destination level, there can be sizable variation in SDI values and the nature of dependency. Panel (b) repeats the analysis for *"Liquefied natural gas"*.[6] Spain, Lithuania, and Malta are particularly dependent on extra-EU imports, due to both a high price elasticity and large expenditure shares. Turning to *"Iron ores and concentrates"* in panel (c), the SDI is high in many EU countries, particularly Belgium, the Netherlands, Poland, and Slovakia. All these countries face high price index elasticities, but the Netherlands and Slovakia additionally report large expenditure shares. In panel (d), the SDI of *"Coffee"* is higher for Germany, Italy, Slovenia, and Finland. These results turn out to be driven more by the price elasticity than by their expenditure shares, similar to the aggregate result for Coffee in Table 4.

Disaggregating welfare effects by destination country reveals that strategic dependencies can vary sharply across EU member states, even for the same product. Moreover, this variation can be driven by fundamentally different channels: high price elasticities in some countries versus large expenditure shares in others. This suggests that uniform EU-wide policy responses may fail to address the heterogeneous nature of member states' vulnerabilities.

Finally, we also identify the extra-EU supplying countries that contribute most to the SDI of these top-4 strategic products, following Eq. (5), in Figure 7. For *"Petroleum oils"* (panel (a)), EU countries are overall highly dependent on imports from Iraq and, to a lower extent, from Azerbaijan. Other extra-EU suppliers, such as Venezuela and Nigeria, contribute less to the SDI. In panel (b), the EU shows a stronger dependency for *"Liquefied natural gas"* imported from Nigeria, Qatar, and Trinidad and Tobago. Other relevant extra-EU suppliers include Algeria, Russia, and Norway. For *"Iron ores and concentrates"* (panel (c)), EU countries rely on imports from several extra-EU countries, especially Brazil and South Africa, but also Ukraine, Canada, Mauritania, Russia, and Liberia. In panel (d), EU countries are mostly vulnerable for *"Coffee"* from Brazil and Honduras, but also from Uganda and Vietnam. Many other extra-EU suppliers have smaller shares.

These cross-country differences in the SDI reflect the variation in our three structural channels: origin-specific taste parameters capturing persistent quality or reputation differences; variation in price levels across origins, such that a shock to a lower-priced supplier has a proportionally larger effect on the price index; and the number of varieties sourced from a given country, where fewer imported varieties imply less scope for within-origin substitution. Decomposing strategic dependencies by extra-EU source country reveals that the suppliers contributing most to aggregate vulnerability for particular goods do not necessarily coincide with the geopolitical rivals that dominate contemporary policy discourse on strategic autonomy, suggesting a potential misalignment between revealed economic exposure and the prevailing focus of policy interventions.

Overall, the SDI ranking partly corroborates but also substantively departs from conventional concentration-based indicators. Mineral fuels and Mining are flagged as strategic by both approaches, but Basic metals — identified as highly strategic by the SDI — appear only moderately concentrated and exposed under existing metrics (see also Table 6). This discrepancy arises because traditional measures do not capture price effects or substitution possibilities across source countries and varieties, and because exposure indicators based purely on trade flows overlook domestic production capacity

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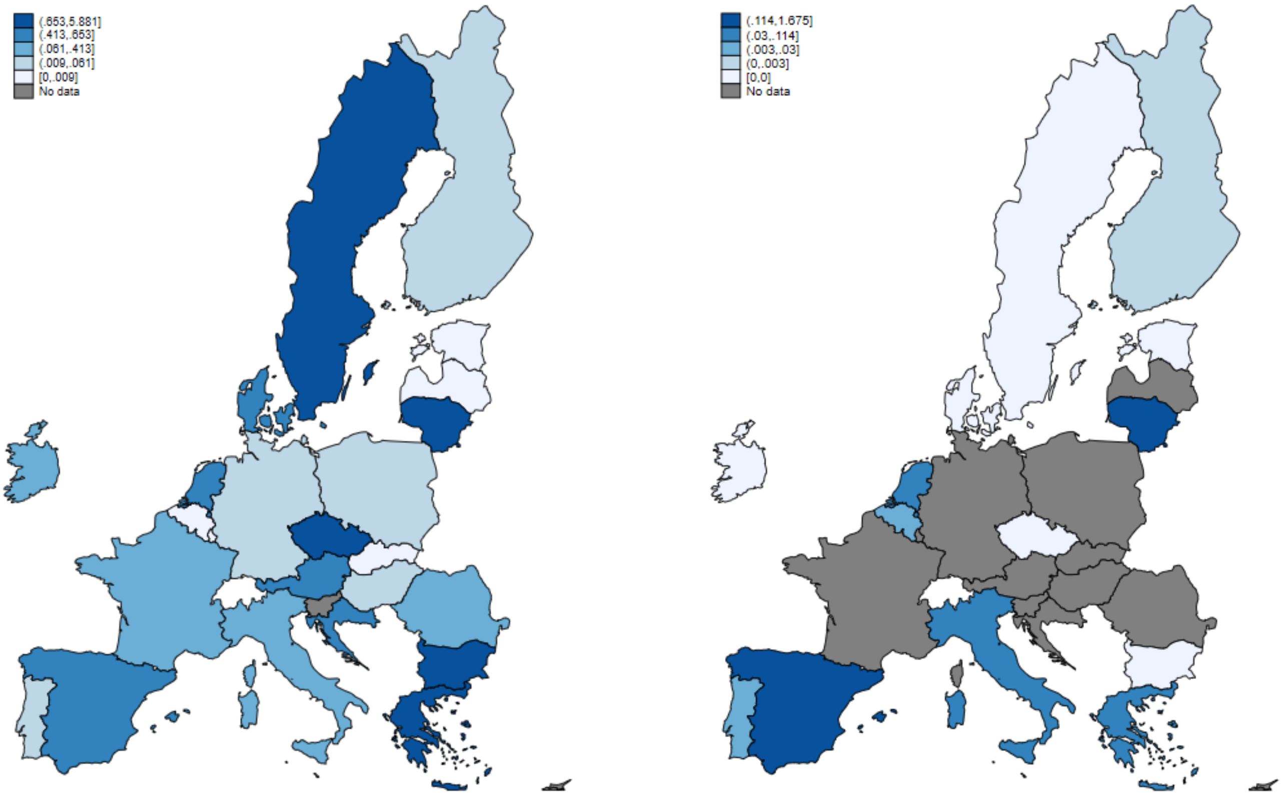
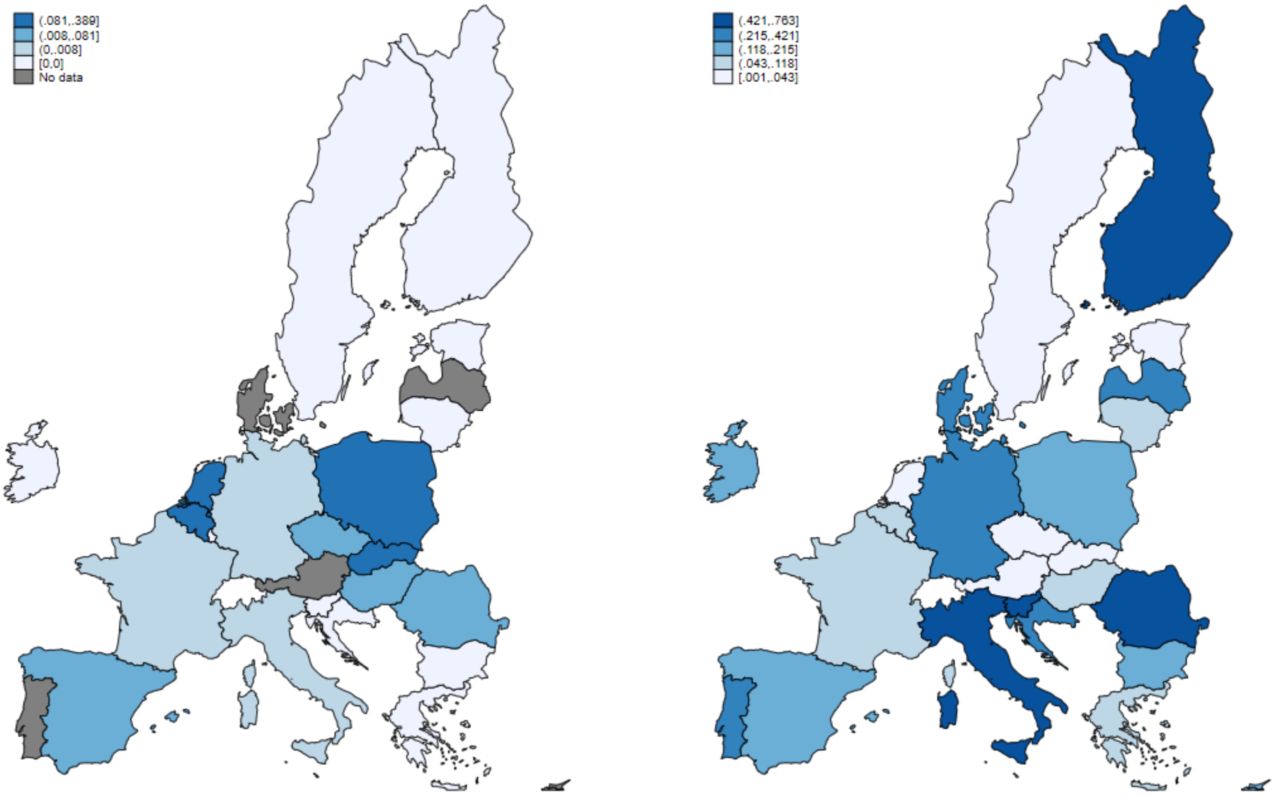
[6] The SDI of liquefied natural gas is not available for several EU countries, as their extra-EU import shares are effectively zero in the data.

Figure 6: SDI for top-4 strategic products by EU country (2019).



(a) Petroleum oils (CN 2709.00.90)

(b) Liquefied natural gas (CN 2711.11.00)



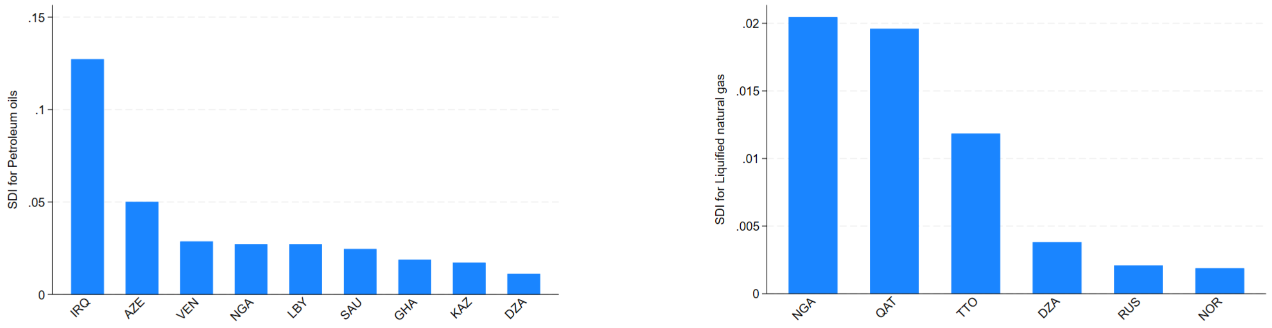
(c) Iron ores and concentrates (CN 2601.11.00)

(d) Coffee (CN 0901.11.00)

and absorption. Conversely, many products in Food, Textiles, and Other manufacturing that rank high under concentration-based measures are identified as less strategic by the SDI. Although these goods may be concentrated and exposed to extra-EU markets, their higher substitutability or lower effective domestic absorption mitigates their welfare relevance.

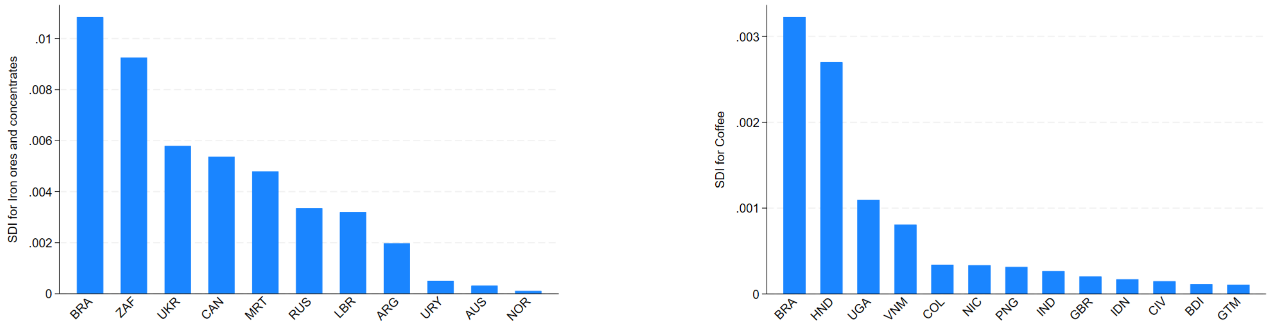
Strikingly, the source-country decomposition reveals that China, the USA, and Russia do not dominate the top of the SDI ranking. EU dependency on China is concentrated in specific basic metals and selected electrical machinery, rather than in textiles and NEC manufacturing where Chinese import shares are highest. Dependency on the USA is driven by particular mineral fuels, precious metals, and chemicals, while Russian dependency centers on natural gas, coal, fertilizers, and semi-finished steel. These findings suggest a potential misalignment between the prevailing focus of EU policy and its revealed economic exposure, reinforcing the case for an economically grounded approach to identifying strategic vulnerabilities.

Figure 7: SDI for top-4 strategic products over extra-EU suppliers (2019).



(a) Petroleum oils (CN 27090090)

(b) Liquefied natural gas (CN 27111100)



(c) Iron ores and concentrates (HS 26011100)

(d) Coffee (CN 09011100)

5.2 Price shocks to critical raw materials

We next evaluate the welfare implications of a 10% increase in EU import prices for goods classified as Critical Raw Materials (CRMs) under the ECRMA (European Union (2024)). The ECRMA identifies critical materials based on two empirical indicators reflecting supply risk and economic importance. We map these to our CN8 product codes, identifying 95 CN8 products as CRMs. Since the CRM classification does not account for substitution elasticities or domestic absorption — the key structural channels underlying the SDI — the set of CRMs does not necessarily coincide with the most strategically dependent products identified by our approach. This exercise therefore provides a direct comparison between the EU's policy-driven classification and a welfare-based assessment of strategic vulnerability.

Table 5 reports the SDI for the top-30 CRM products in 2019. The ranking spans both extraction and processing stages, covering Mining (HS 25–26) and Basic metals (HS 71–81), with *Coking coal*, *Aluminium (unwrought)*, *Copper (refined)*, *Aluminium ores*, and *Nickel (unwrought)* at the top. SDI values (column 3) are an order of magnitude smaller than those reported in Table 4. This largely reflects the fact that most CRMs account for very small shares of total EU consumption (column 5): these are goods that matter for specific industrial supply chains, but whose direct weight in total expenditures — and hence in aggregate welfare — remains limited. Nevertheless, several products display very high price index elasticities (column 4) despite their modest expenditure shares. *Aluminium ores* (0.377), *Unwrought antimony* (0.152), and *Coking coal* (0.119) all exhibit large price effects from limited substitution possibilities and strong exposure to supply disruptions. For these products, even moderate increases in expenditure shares — driven by e.g. the green transition or shifts in industrial policy — could translate into substantially larger welfare effects.

Overall, Table 5 highlights an important distinction between "criticality" as defined by concentration and supply risk criteria and strategic dependency as measured through a welfare-based framework. Even among CRMs, the SDI values decline rapidly: the top-ranked CRM product (*Coking coal*, SDI of 0.016) is already over twenty times smaller than *Petroleum oils*, and the majority of the 95 CRM products exhibit SDI values several orders of magnitude below the overall top-30 threshold. The key reason is that the aggregate welfare impact of a price shock depends crucially on the interaction between expenditure shares and structural demand parameters, a channel that concentration-based indicators do not capture. As a result, while many officially designated CRMs generate modest welfare losses under uniform price increases, several goods outside the CRM list — such as *Petroleum oils*, *Coffee*, and *Cocoa beans* — prove more strategically relevant when evaluated within a structural framework.

Table 5: Top-30 Critical Raw Materials products (2019).

Product (CN8)	HS2 code	$SDI_{kt}(\omega)$	Price index elasticity	Expenditure share (%)
Coking coal "ECSC", whether or not pulverized, non-agglomerated	27	.016	.119	0.06
Aluminium, not alloyed, unwrought	76	.015	.108	0.07
Copper, refined, in the form of cathodes and sections of cathodes	74	.007	.065	0.06
Aluminium ores and concentrates	26	.005	.377	0.007
Nickel, not alloyed, unwrought	75	.003	.060	0.03
Natural calcium and natural aluminium phosphates, ground	25	.002	.055	0.004
Natural calcium and natural aluminium phosphates, unground	25	.001	.049	0.002
Unwrought antimony; antimony powders	81	.001	.152	0.002
Waste and scrap of platinum	71	.001	.018	0.002
Copper ores and concentrates	26	.0003	.005	0.07
Cobalt mattes and other intermediate products; unwrought cobalt; cobalt powders	81	.0002	.015	0.006
Manganese ores and concentrates, with a manganese content of >= 20%	26	.0002	.024	0.003
Copper, unrefined; copper anodes for electrolytic refining	74	.0002	.009	0.008
Nickel ores and concentrates	26	.0002	.001	0.003
Platinum, unwrought or in powder form	71	.0002	.008	0.01
Ash and residues containing mainly titanium	26	.0001	.001	0.001
Unwrought nickel alloys	75	.0001	.078	0.002
Palladium, unwrought or in powder form	71	.0001	.005	0.008
Unwrought magnesium, containing < 99,8% by weight of magnesium	81	.0001	.045	0.002
Titanium waste and scrap	81	.0001	.037	0.003
Unwrought magnesium, containing >= 99,8% by weight of magnesium	81	4.5e-05	.046	0.002
Powders and flakes, of nickel (excl. nickel oxide sinters)	75	3.5e-05	.014	0.002
Unwrought titanium; titanium powders	81	3.2e-05	.014	0.003
Bars, rods, wire and sections, (..), of a thickness of > 0,15 mm, of platinum	71	2.3e-05	.005	0.003
Catalysts in the form of wire cloth or grill, of platinum	71	1.7e-05	.006	0.001
Platinum in semi-manufactured forms	71	1.2e-05	.006	0.001
Palladium in semi-manufactured forms	81	1.0e-05	.006	0.001
Tungsten waste and scrap	81	9.9e-06	.004	0.001
Silicon containing < 99,99% by weight of silicon	28	9.1e-06	.001	0.008
Iridium, osmium and ruthenium, unwrought or in powder form	71	8.6e-06	.006	0.001

Note: $SDI_{kt}(\omega)$ is the Strategic Dependency Index calculated for each CN8 product ω mapped to Critical Raw Materials. The price index elasticity is computed as the EU weighted average of the price index changes in EU countries in response to extra-EU shocks. The expenditure share is calculated as the EU expenditure on each good from extra-EU countries in the total EU expenditure (i.e., imports plus domestic production).

6 Comparison to existing measures

A key motivation for a welfare-based measure of strategic dependence is that commonly used concentration-based indicators may misidentify which goods are truly strategic. We evaluate this directly by contrasting the SDI with commonly used empirical indicators of strategic dependence based on trade data. These indicators often rely on concentration metrics, but without notions of demand or substitution, or the possibility to perform welfare evaluations. These comparisons show that, while imports can be strongly concentrated in key supplying countries, import concentration alone is not sufficient to identify welfare-relevant strategic dependence as measured by our SDI.

6.1 Empirical concentration and exposure measures

Currently, there are several empirical indicators that assess a country's dependence on imports from third countries (see e.g., Vicard and Wibaux (2023) for an overview). Typical indicators combine two dimensions recovered directly from trade data: (i) concentration, measured by the Herfindahl–Hirschman Index (HHI) of imports across source countries, and (ii) exposure, measured by the share of these imports in total imports, exports, or domestic absorption.

For example, the European Commission (2021) classifies a product as strategic when three sub-indicators jointly exceed predefined thresholds: (i) HHI of concentration of EU imports across extra-EU countries exceeding 0.4; (ii) the share of EU imports from extra-EU countries in total EU imports being larger than 0.5; and (iii) the ratio of extra-EU imports over total EU exports being above one.[7] Similarly, Berthou et al. (2024) consider two product-level measures of concentration to study the import vulnerability of OECD countries: the HHI of OECD imports across origin countries and the HHI of global exports across supplying countries. Finally, the EU Critical Raw Materials Act (European Union (2024)) provides two measures to identify critical raw materials for the EU as described before.

However, import concentration and strategic dependency are distinct concepts. In particular, concentration measures do not identify how easily demand can be reallocated across origins or varieties following a price shock. In our framework, the welfare impact of a supply disruption depends not only on the expenditure share of a supplier, but also on the elasticities of substitution and origin-destination-specific taste shifters. A highly concentrated product may therefore generate limited welfare losses if it is easy to substitute away from it, while a moderately concentrated product with low substitutability may entail large welfare costs.

To highlight these differences, we first reconstruct the most commonly used empirical indicators of import concentration and exposure, computed at the CN8 level and averaged over the period 2002–2021. Table 6 confirms that EU imports are often highly concentrated across extra-EU suppliers. For the median product within its industry, the largest extra-EU supplying country accounts for roughly half of EU imports (column 3), consistent with indicators used by Amaral et al. (2022) and the ECRMA (European Union (2024)). Concentration is particularly pronounced in *Food* (0.70) and *Petroleum and mineral fuels* (0.57), implying a dominant role of single third-country suppliers in these sectors. Columns 4 to 6 further report the three sub-indicators used by European Commission (2021). The median HHI of extra-EU imports across source countries equals 0.35 (column 4), and is again highest in *Food* (0.54) and *Petroleum and mineral fuels* (0.42). The median share of extra-EU imports in total EU imports equals 31% (column 5), now with particularly high values in *N.E.C. and recycling* (0.51), *Electrical equipment* (0.45), *Mining* (0.44), and *Textiles* (0.44). Similarly, the median ratio of extra-EU imports to EU exports (column 6) equals 0.78 overall, and exceeds 2 in *Petroleum and mineral fuels* (2.55) and *Mining* (2.22). These statistics would naturally lead to the conclusion that sectors such as Food, Petroleum and mineral fuels, Textiles, and Mining are among the most strategically dependent segments of EU trade. However, these concentration metrics do not incorporate any demand parameters or the welfare consequences of price shocks, and once these margins are taken into account, the ranking of strategically important goods changes substantially.

6.2 Comparison to the SDI

Next, Table 7 shows the correlation between our SDI and the most common empirical indicators. More strategic products are not concentrated in few extra-EU origin countries (lower HHI), are generally imported more from extra-EU countries (higher share of extra-EU imports), and they are hard to substitute with EU internal production (extra-EU imports larger than EU exports). The negative

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[7] The last sub-indicator serves as a proxy for EU domestic production, for which data is not readily available at this level of granularity.

Table 6: Concentration and exposure of extra-EU imports by ISIC industry.

Sector	ISIC4 codes	Median first source-country share	Median HHI	Median extra-EU/ total imports	Median extra-EU/ total exports
Agriculture	100–999	0.55	0.39	0.25	1.10
Mining	1000–1499	0.51	0.34	0.44	2.22
Food	1500–1699	0.70	0.54	0.16	0.74
Textiles	1700–1999	0.46	0.30	0.44	1.22
Wood	2000–2099	0.51	0.34	0.29	1.16
Paper	2100–2299	0.51	0.35	0.19	0.53
Petroleum and mineral fuels	2300–2399	0.57	0.42	0.38	2.55
Chemicals	2400–2499	0.53	0.38	0.33	0.87
Rubber and plastics	2500–2599	0.41	0.26	0.24	0.69
Non-metallic minerals	2600–2699	0.45	0.28	0.28	0.60
Basic metals	2700–2799	0.49	0.34	0.24	0.85
Fabricated metals	2800–2899	0.44	0.28	0.30	0.72
Machinery	2900–3099	0.43	0.28	0.30	0.34
Electrical equipment	3100–3399	0.44	0.28	0.45	0.86
Transport equipment	3400–3599	0.49	0.34	0.26	0.50
N.E.C. and recycling	3600–3800	0.57	0.38	0.51	1.44
Total		0.51	0.35	0.31	0.78

correlation between the SDI and the HHI is an empirical finding that reflects the joint distribution of import concentration and domestic absorption shares across products. In the data, products with high import concentration tend to have small expenditure shares in total absorption, while products sourced from many origins tend to be economically important goods where total extra-EU penetration is high.

Table 7: Correlations with empirical measures.

Variable	$\ln SDI$	$\ln HHI$	$\ln \frac{\text{Extra-EU imports}}{\text{Total EU imports}}$	$\ln \frac{\text{Extra-EU imports}}{\text{Total EU exports}}$
$\ln SDI$	1.00			
$\ln HHI$	-0.35	1.00		
$\ln \frac{\text{Extra-EU imports}}{\text{Total EU imports}}$	0.40	-0.22	1.00	
$\ln \frac{\text{Extra-EU imports}}{\text{Total EU exports}}$	0.17	0.06	0.62	1.00

Note: This table reports the pairwise correlation coefficients between the log SDI and three empirical measures used by European Commission (2021).

We further compare the SDI with the composite indicator of the European Commission, and highlight two key differences.[8] First, the overlap between the two classifications is limited. Among the top-30 products ranked by the SDI in 2019 (Table 4), only four are classified as strategic under the European Commission (2021) methodology. The discrepancy runs in both directions. On one hand, the European Commission labels as strategic many products in *NEC manufacturing*, *Textiles*, *Agriculture*, and *Food* — sectors that, despite high import concentration, exhibit high substitution

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[8] Using the Commission's methodology with the composite indicator, we identify 831 CN8 products as being strategic in 2002, and 891 products in 2021. Strategic goods account for around 11% of all CN8 goods in any given year. The European Commission (2021) identifies around 400 strategic goods at the HS6 level in 2019, versus 860 in the Comext CN8 data. This difference is attributed to the different granularity of product codes, as well as different harmonization of product codes over time as we employ CN8+ codes.

elasticities and limited welfare impact under a uniform price shock. On the other hand, several high-SDI goods, such as *Iron ores*, *Aluminium oxide*, *Refined copper*, and *Natural gas*, are not identified as strategic in the Commission's methodology because their HHI falls below the 0.4 threshold. Yet most of these products display low substitution elasticities and high preference shifters for extra-EU imports, generating substantial welfare exposure. This two-way mismatch indicates that import concentration is neither necessary nor sufficient for welfare-relevant strategic dependence.

Second, threshold-based indicators are inherently volatile over time. Because products are classified as strategic only when concentration or exposure metrics exceed predefined cutoffs, small fluctuations in trade flows may move products in and out of the "strategic" category without reflecting structural changes in dependence. In our data, only 23% of goods classified as strategic in 2002 remain so in 2019. A strategic dependency measure on which two-thirds of designated products lose their status within a decade provides an unstable foundation for long-term industrial or trade policy. By contrast, because the SDI varies continuously with demand parameters and expenditure shares, it produces substantially more stable rankings over time: 22 of the top-30 products in 2019 also appear in the top-30 in 2002 (see Table 4 vs. Table A4).

Taken together, these results indicate that concentration-based indicators and the SDI capture fundamentally different dimensions of import dependence. While concentration metrics are informative about the distribution of trade flows, they do not incorporate preferences, substitution possibilities or domestic absorption, and as a result can both overstate and understate welfare-relevant strategic vulnerability. By embedding trade exposure within a structural demand framework, the SDI provides a theory-consistent, continuous, and temporally stable measure of strategic dependence that is better suited to inform long-term policy design.

7 Conclusion

This paper develops a welfare-based measure of strategic trade dependence — the Strategic Dependency Index (SDI) — that maps structural demand primitives into the sensitivity of consumer prices to product-level import price shocks, and is additively decomposable across products, source, and destination countries. Unlike existing empirical indicators that rely on concentration metrics and ad hoc thresholds, the SDI is derived from a cost-of-living index and explicitly accounts for substitution elasticities across source countries and varieties, origin-destination-specific preference shifters, and expenditure shares in domestic absorption. We estimate these parameters using highly disaggregated CN8-level trade data for the EU27 over the period 2002–2021, instrumented to address the endogeneity of prices and expenditure shares.

Three sets of findings emerge. First, the products generating the largest welfare losses under import price shocks — petroleum oils, liquefied natural gas, iron ores, and selected basic metals — partly overlap with but also substantively depart from those flagged by conventional indicators. The SDI identifies basic metals as highly strategic despite their moderate import concentration, while many goods in textiles, food, and NEC manufacturing that rank high under concentration-based measures prove less welfare-relevant due to their high substitutability. Only four of the top-30 SDI products are classified as strategic under the European Commission's composite indicator, and the SDI ranking is substantially more stable over time: 22 of the top-30 products in 2019 also appeared in 2002, compared to only 23% of goods retaining their strategic classification under threshold-based measures. Second, disaggregating by EU member state reveals that strategic dependencies vary sharply across countries even for the same product, driven by fundamentally different channels: high price elasticities in some countries versus large expenditure shares in others. This heterogeneity implies that uniform EU-wide policy responses may fail to address the diverse nature of member states' vulnerabilities. Third, decomposing the SDI by extra-EU source country shows that the suppliers contributing most to aggregate welfare exposure (Iraq and Azerbaijan for petroleum, Nigeria and Qatar for natural gas, Brazil and South Africa for iron ores) do not necessarily coincide with the geopolitical rivals that dominate contemporary policy discourse on strategic autonomy. Strikingly, China, the USA, and Russia do not dominate the top of the SDI ranking — EU dependency on these countries is concentrated in specific product categories rather than in the broad sectors where their import shares are highest.

These findings carry direct policy implications. For products where high SDI values are driven primarily by large expenditure shares rather than low substitutability, such as petroleum oils and natural gas, diversification of extra-EU import sources represents a viable strategy to reduce strategic dependency, as close substitutes across supplying countries are relatively available. Conversely, for products characterized by low substitution elasticities, such as mining products, certain chemicals, and critical raw materials like aluminium ores and antimony, diversification alone may prove insufficient, and policies aimed at expanding domestic production capacity, recycling, or developing synthetic alternatives may be more effective. The SDI's additive decomposability across products, destinations, and source countries provides a tractable framework for evaluating such targeted interventions.

We conclude by discussing the scope of the framework and avenues for further research. The SDI is a first-order, partial equilibrium measure. This choice is deliberate: by anchoring the index in the cost-of-living framework, the SDI remains tractable, transparent, and additively decomposable across products, countries, and source origins. A full general equilibrium model would require additional assumptions on production technology and factor markets that risk obscuring the demand-side mechanisms at the core of our contribution, while introducing parameters that are difficult to estimate at the granularity of CN8 products. Importantly, because the SDI abstracts from input-output propagation through production networks, it provides a conservative assessment of strategic vulnerability: accounting for supply chain amplification would plausibly reinforce rather than overturn the SDI ranking, since the goods identified as most strategic — petroleum, basic metals, and mining products — are precisely those that serve as key upstream inputs in EU manufacturing. While we do account for intermediates in total domestic absorption, extending the framework to incorporate detailed production network data and quantify the amplification of import price shocks through value chains constitutes a natural next step. This, however, requires granular data on both trade and production at the CN8 or Prodcom level that are not yet widely available. Beyond goods trade, extending the analysis to digital and services markets represents an important frontier, as these sectors may exhibit extreme concentration with very low substitutability (for instance in cloud computing or semiconductor design services) yet require data beyond merchandise trade statistics. Finally, while our demand parameters are estimated on a twenty-year panel and shown to be stable, the framework is inherently backward-looking: shifts in technology, the green transition, or geopolitical realignments may alter substitution patterns and expenditure shares in ways that historical estimates do not fully anticipate. Combining the SDI with forward-looking scenario analysis represents a promising avenue for future research.

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A Model derivations

This appendix shows that, under homothetic preferences, the welfare effect of a price change equals the elasticity of the relevant price index with respect to that price.

The representative consumer in country i at time t maximizes utility over industry-level consumption bundles:

$$\max_{\{Q_{i,kt}\}_{k\in K}} U_{i,t}(Q_{i,1t}, \ldots, Q_{i,Kt}) \quad \text{s.t.} \quad \sum_{k=1}^{K} P_{i,kt} Q_{i,kt} = Y_{i,t}, \tag{8}$$

where $P_{i,kt}$ denotes the price index of industry k in country i, and $Y_{i,t}$ is total expenditure. Preferences are assumed to be homothetic, strictly increasing, and concave. Homotheticity implies that the indirect utility can be written as a monotonic transformation of real expenditure:

$$v_{i,t}(\{P_{i,kt}\}, Y_{i,t}) = T\left(\frac{Y_{i,t}}{P_{i,t}}\right), \tag{9}$$

where $T(\cdot)$ is a strictly increasing function and $P_{i,t}$ is the country-level price index implied by preferences. As goods are aggregated using a nested CES structure across origin countries and varieties for each industry k, the industry-level indirect utility is:

$$v_{i,kt}(\{p_{ji,kt}(\omega)\}, Y_{i,kt}) = T\left(\frac{Y_{i,kt}}{P_{i,kt}}\right), \tag{10}$$

where $P_{i,kt}$ is the industry-level price index. Inverting this expression yields the expenditure function:

$$e_{i,kt}(\{p_{ji,kt}(\omega)\}, u) = T^{-1}(u)\, P_{i,kt}, \tag{11}$$

which gives the minimum expenditure required to achieve utility level u at prices $p_{ji,kt}(\omega)$. Then we define a money-metric utility evaluated at reference prices p^r as:

$$m_{i,kt}(p^r, \{p_{ji,kt}(\omega)\}, Y_{i,kt}) = e_{i,kt}\left(p^r, v_{i,kt}(\{p_{ji,kt}(\omega)\}, Y_{i,kt})\right). \tag{12}$$

Substituting the expenditure function and indirect utility equations yields

$$m_{i,kt}(p^r, \{p_{ji,kt}(\omega)\}, Y_{i,kt}) = T^{-1}\left(T\left(\frac{Y_{i,kt}}{P_{i,kt}(p_{ji,kt}(\omega))}\right)\right) P_{i,kt}(p^r) = Y_{i,kt} \frac{P_{i,kt}(p^r)}{P_{i,kt}(p_{ji,kt}(\omega))}. \tag{13}$$

Finally, we measure the welfare impact of a change in the price of variety ω produced in country j and industry k as the elasticity of the money-metric utility with respect to that price:

$$-\frac{\partial \ln m_{i,kt}(p^r, \{p_{ji,kt}(\omega)\}, Y_{i,kt})}{\partial \ln p_{ji,kt}(\omega)}. \tag{14}$$

Using the expression for money-metric utility, this reduces to

$$-\frac{\partial \ln m_{i,kt}}{\partial \ln p_{ji,kt}(\omega)} = \frac{\partial \ln P_{i,kt}}{\partial \ln p_{ji,kt}(\omega)}. \tag{15}$$

B Additional empirical results

Table A1: Estimated trade elasticity with CN8-level EU export price by ISIC industry.

Sector	ISIC4 codes	$\sigma_k - 1$	Obs.	Weak Ident. test
Agriculture	100-999	1.827 (0.108)	1,035,166	673
Mining	1000-1499	2.575 (0.117)	193,932	463
Food	1500-1699	2.653 (0.098)	2,366,319	1,790
Textiles	1700-1999	2.105 (0.079)	3,781,132	1,627
Wood	2000-2099	3.617 (0.110)	362,886	349
Paper	2100-2299	3.983 (0.276)	651,826	416
Petroleum, mineral fuels	2300-2399	3.600 (0.201)	117,201	326
Chemicals	2400-2499	2.075 (0.037)	2,020,299	3,511
Rubber and plastics	2500-2599	4.012 (0.083)	1,270,434	1,082
Non-metallic minerals	2600-2699	2.543 (0.053)	738,803	1,028
Basic metals	2700-2799	4.162 (0.203)	1,022,469	417
Fabricated metals	2800-2899	2.566 (0.101)	1,556,970	1,321
Machinery	2900-3099	2.058 (0.081)	2,470,163	580
Electrical equipment	3100-3399	1.660 (0.101)	2,492,555	1,379
Transport equipment	3400-3599	1.073 (0.081)	591,104	346
N.E.C. and recycling	3600-3800	1.814 (0.156)	1,127,135	424

Note: The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

Table A2: Estimated love for variety elasticity with number of CN8 products by ISIC industry.

Sector	ISIC4 codes	$\frac{\sigma_k-1}{\gamma_k-1}$	γ_k	Obs.	Weak Ident. test
Agriculture	100-999	0.661	3.760	1,246,737	712
		(0.016)			
Mining	1000-1499	0.590	5.142	286,835	158
		(0.015)			
Food	1500-1699	0.687	5.228	2,762,006	1,335
		(0.011)			
Textiles	1700-1999	0.797	3.468	6,350,635	5,354
		(0.079)			
Wood	2000-2099	0.961	3.847	362,886	349
		(0.027)			
Paper	2100-2299	0.913	4.850	909,676	216
		(0.038)			
Petroleum, mineral fuels	2300-2399	0.579	7.268	117,685	74
		(0.025)			
Chemicals	2400-2499	0.709	3.992	2,620,733	3,312
		(0.024)			
Rubber and plastics	2500-2599	0.835	5.259	1,660,561	1,594
		(0.052)			
Non-metallic minerals	2600-2699	0.844	3.691	977,489	897
		(0.019)			
Basic metals	2700-2799	0.772	6.465	1,197,876	316
		(0.024)			
Fabricated metals	2800-2899	0.644	4.735	2,021,799	1,543
		(0.032)			
Machinery	2900-3099	0.816	3.261	2,955,171	204
		(0.064)			
Electrical equipment	3100-3399	0.779	3.076	2,881,042	1,140
		(0.053)			
Transport equipment	3400-3599	0.938	2.295	669,707	152
		(0.061)			
N.E.C. and recycling	3600-3800	0.906	2.588	1,721,466	620
		(0.023)			

Note: The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

Table A3: First stage results for all sectors and by ISIC industry.

Dependent variables (logs):		Import price			Expenditure share				
Sector	ISIC4 codes	$p^e_{j,kt}(\omega)$	$z^1_{ji,kt}$	$z^2_{i,kt}(\omega)$	$p^e_{j,kt}(\omega)$	$z^1_{ji,kt}$	$z^2_{i,kt}(\omega)$	Obs.	Weak Ident. test
Agriculture	100-999	0.095	-0.029	-0.036	-0.171	1.446	0.693	1,246,737	299.8
		(0.004)	(0.004)	(0.004)	(0.011)	(0.013)	(0.016)		
Mining	1000-1499	0.099	-0.131	-0.115	-0.241	1.798	0.663	286,835	132.5
		(0.008)	(0.014)	(0.010)	(0.020)	(0.031)	(0.025)		
Food	1500-1699	0.119	-0.020	-0.061	-0.337	1.461	0.627	2,762,006	839.5
		(0.003)	(0.003)	(0.005)	(0.012)	(0.012)	(0.026)		
Textiles	1700-1999	0.102	-0.015	-0.008	-0.171	1.041	0.740	6,350,635	1,828.4
		(0.001)	(0.005)	(0.004)	(0.008)	(0.018)	(0.016)		
Wood	2000-2099	0.107	0.018	-0.079	-0.301	1.424	0.651	316,247	158.5
		(0.007)	(0.010)	(0.014)	(0.034)	(0.022)	(0.019)		
Paper	2100-2299	0.111	-0.040	-0.074	-0.383	1.337	0.859	909,676	181.8
		(0.008)	(0.015)	(0.013)	(0.031)	(0.027)	(0.029)		
Petroleum, mineral fuels	2300-2399	0.084	-0.110	-0.193	-0.280	2.020	0.759	117,685	33.5
		(0.010)	(0.012)	(0.012)	(0.029)	(0.059)	(0.044)		
Chemicals	2400-2499	0.155	-0.074	-0.112	-0.323	1.479	0.740	2,620,732	778.1
		(0.003)	(0.007)	(0.008)	(0.006)	(0.015)	(0.016)		
Rubber and plastics	2500-2599	0.147	-0.070	-0.097	-0.512	1.344	0.664	1,660,561	349.1
		(0.004)	(0.011)	(0.010)	(0.008)	(0.021)	(0.028)		
Non-metallic minerals	2600-2699	0.143	-0.035	-0.064	-0.316	1.383	0.670	977,489	521.5
		(0.005)	(0.011)	(0.012)	(0.012)	(0.017)	(0.019)		
Basic metals	2700-2799	0.078	0.001	-0.079	-0.238	1.424	0.772	1,331,117	98.7
		(0.004)	(0.008)	(0.005)	(0.016)	(0.017)	(0.015)		
Fabricated metals	2800-2899	0.125	-0.085	0.016	-0.308	1.449	0.802	2,021,799	161.1
		(0.003)	(0.018)	(0.013)	(0.016)	(0.027)	(0.023)		
Machinery	2900-3099	0.102	-0.116	-0.005	-0.194	1.228	0.545	2,955,171	113.9
		(0.007)	(0.017)	(0.009)	(0.012)	(0.031)	(0.025)		
Electrical equipment	3100-3399	0.132	-0.086	0.023	-0.209	1.354	0.736	2,881,042	814.5
		(0.004)	(0.013)	(0.010)	(0.013)	(0.035)	(0.039)		
Transport equipment	3400-3599	0.101	-0.029	-0.014	-0.140	1.526	.558	669,705	61.8
		(0.008)	(0.011)	(0.014)	(0.015)	(0.032)	(0.026)		
N.E.C. and recycling	3600-3800	0.117	0.018	0.037	-0.169	1.292	0.818	1,721,466	241.1
		(0.005)	(0.007)	(0.006)	(0.012)	(0.014)	(0.029)		
All sectors		**0.117**	**-0.036**	**-0.038**	**-0.263**	**1.294**	**0.694**	**29,712,806**	**2,044.4**
		(0.002)	(0.003)	(0.003)	(0.005)	(0.012)	(0.008)		

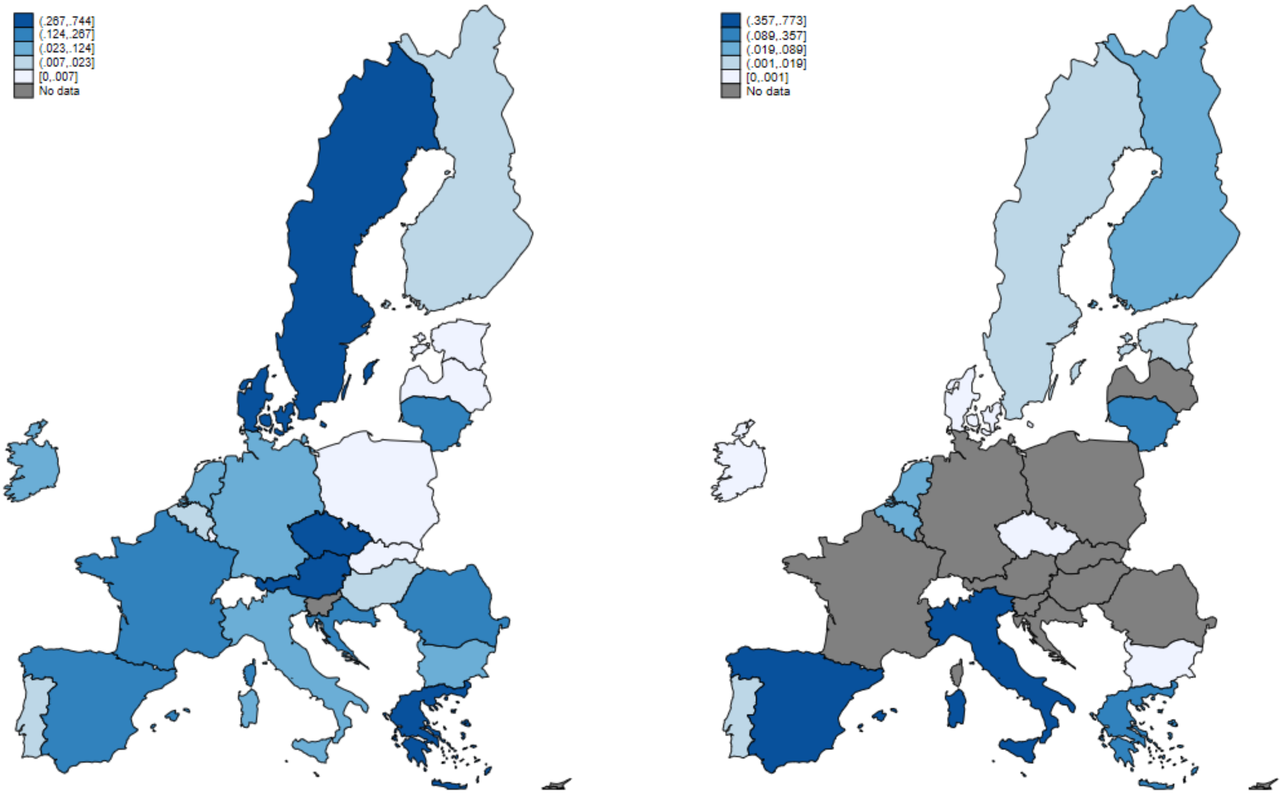
Note: The first-stage estimation is conducted for all sectors and, separately, for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

Table A4: Top-30 strategic products ranked by the Strategic Dependency Index in 2002.

Product (CN8)	HS2 code	$SDI_{kt}(\omega)$	Price index elasticity	Expenditure share (%)
Petroleum oils and oils from bituminous minerals	27	.470	.248	1.90
Non-agglomerated iron ores and concentrates "ECSC"	26	.020	.311	0.04
Aluminium, not alloyed, unwrought	76	.017	.198	0.07
Coffee (excl. roasted and decaffeinated)	09	.012	.254	0.04
Coking coal "ECSC", whether or not pulverized, non-agglomerated	27	.007	.115	0.03
Copper, refined, in the form of cathodes and sections of cathodes	74	.006	.056	0.05
Cocoa beans, whole or broken, raw or roasted	18	.006	.213	0.03
Aluminium oxide (excl. artificial corundum)	28	.005	.348	0.01
Oil-cake and other solid residues from the extraction of soya-bean oil	23	.004	.049	0.08
Natural gas, liquefied	27	.004	.014	0.04
Nickel, not alloyed, unwrought	75	.003	.104	0.03
Natural gas in gaseous state	27	.003	.008	0.14
Bituminous coal "ECSC", whether or not pulverized, non-agglomerated	27	.002	.085	0.004
White sugar, containing >= 99,5% sucrose	17	.002	.172	0.005
Cotton, neither carded nor combed	52	.002	.193	0.01
Maize (excl. seed)	10	.002	.122	0.004
Gold, incl. gold plated with platinum, unwrought	71	.002	.037	0.07
Aluminium ores and concentrates	26	.002	.377	0.01
Technically specified natural rubber "TSNR"	40	.002	.304	0.01
Crude palm oil	15	.002	.124	0.01
Natural calcium and natural aluminium phosphates, ground	25	.002	.062	0.003
Natural calcium and natural aluminium phosphates, unground	25	.001	.070	0.01
Anhydrous ammonia	28	.001	.152	0.004
Natural rubber in primary forms or in plates, sheets or strip	40	.001	.128	0.01
Agglomerated iron ores and concentrates "ECSC"	26	.001	.062	0.02
Sea-going cruise ships, excursion boats and similar vessels	89	.001	.013	0.01
Greasy shorn wool, neither carded nor combed	51	.001	.060	0.01
Urea, whether or not in aqueous solution, containing > 45% nitrogen	31	.001	.109	0.01
Sea-going vessels for the transport of goods and persons	89	.001	.038	0.02
Natural honey	04	.001	.129	0.004

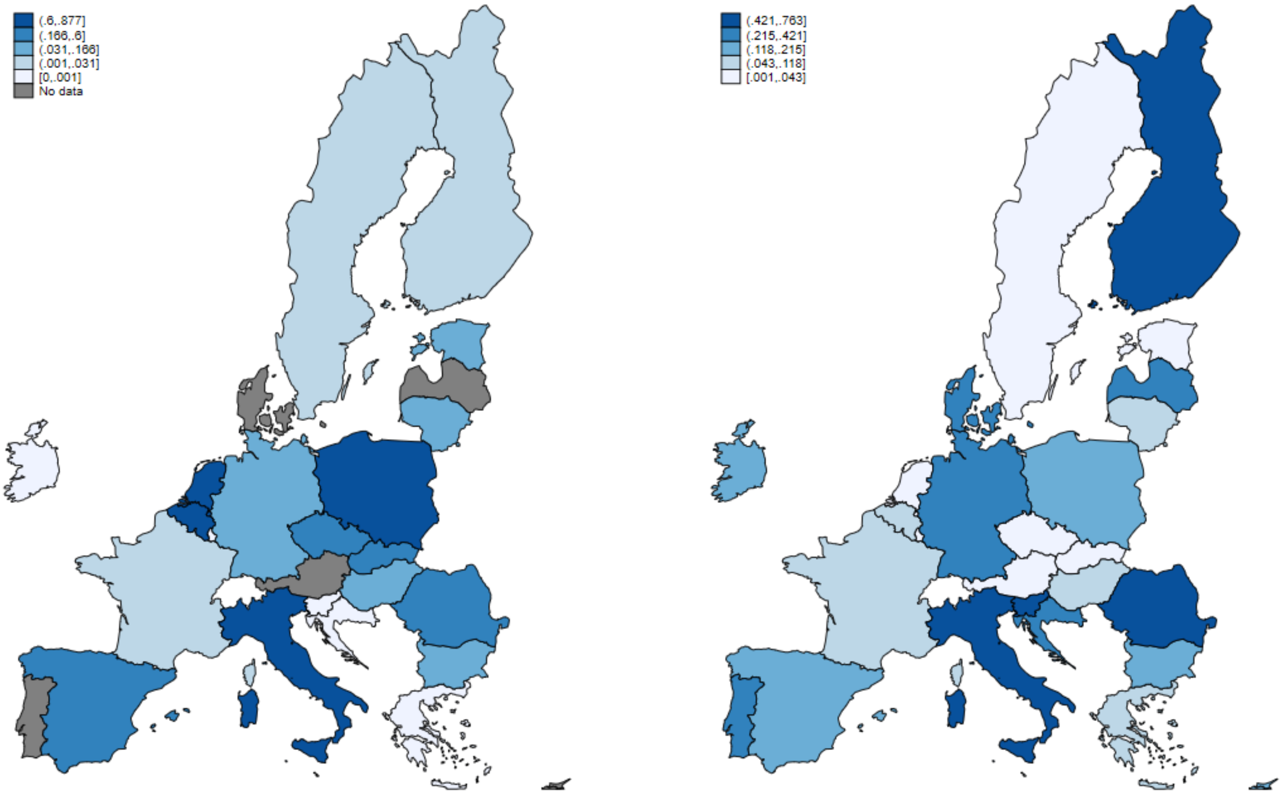
Note: $SDI_{kt}(\omega)$ is the Strategic Dependency Index calculated for each CN8 product ω in sector k and year t. The price index elasticity is computed as the EU weighted average of the price index changes in EU countries. The expenditure share is calculated as the EU expenditure on each good from extra-EU countries in the total EU expenditure (i.e., imports plus domestic production).

Figure A1: Price index elasticity for top-4 strategic products by EU country (2019).



(a) Petroleum oils (CN 27090090)

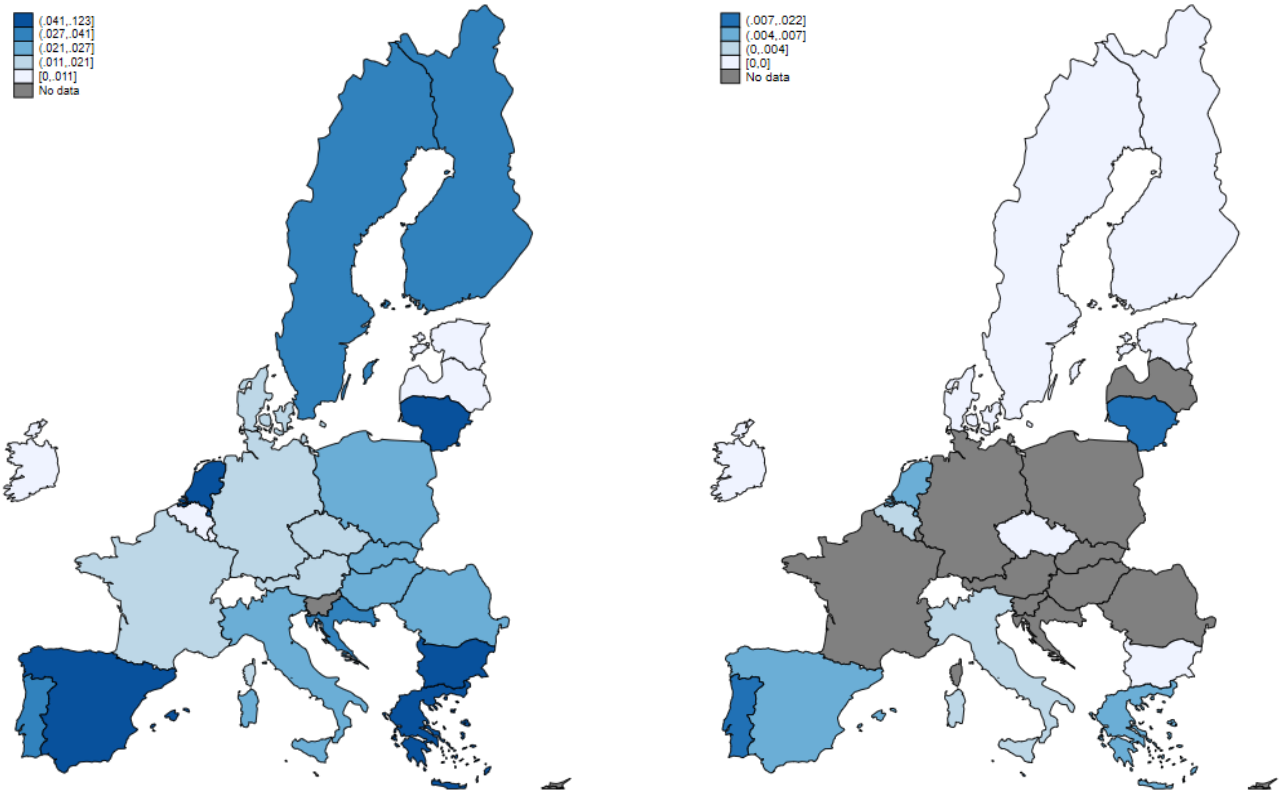
(b) Liquefied natural gas (CN 27111100)



(c) Iron ores and concentrates (HS 26011100)

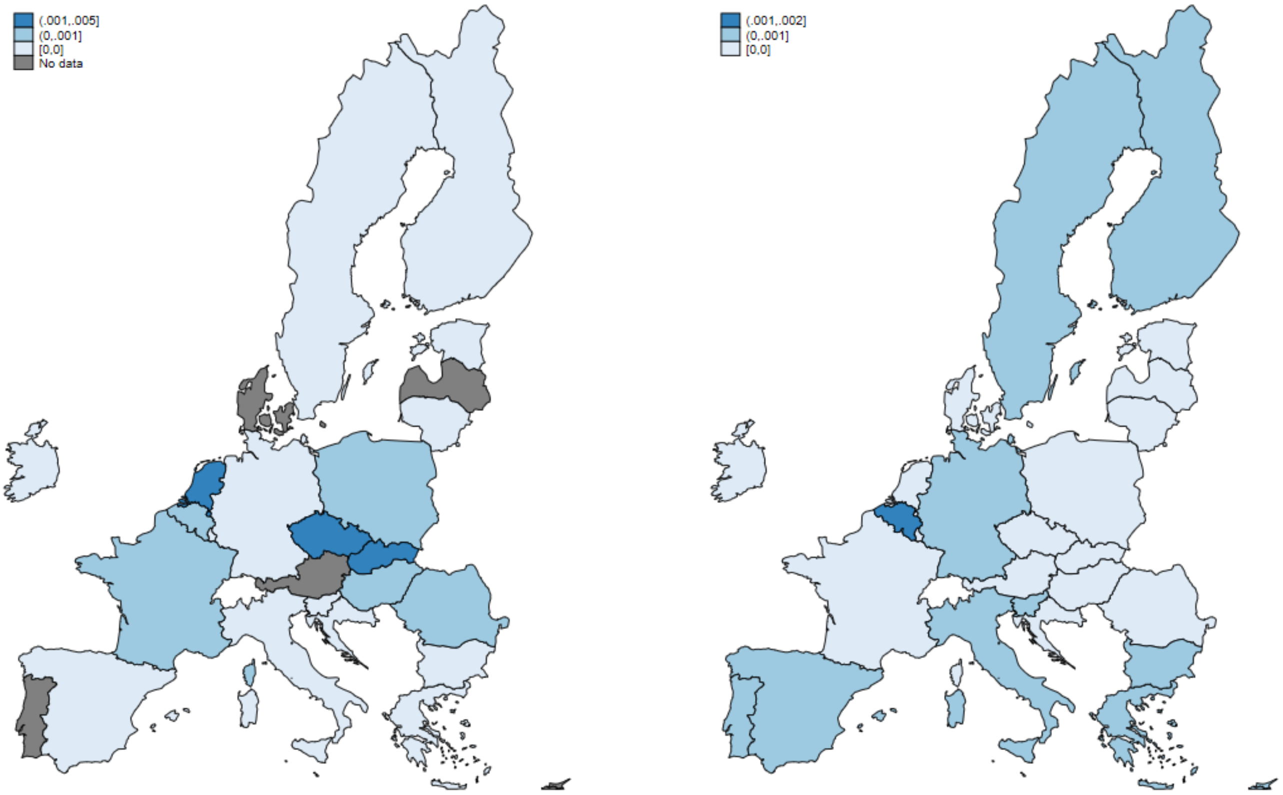
(d) Coffee (CN 09011100)

Figure A2: Expenditure share for top-4 strategic products by EU country (2019).



(a) Petroleum oils (CN 27090090)

(b) Liquefied natural gas (CN 27111100)



(c) Iron ores and concentrates (HS 26011100)

(d) Coffee (CN 09011100)